DE MONTFORT UNIVERSITY

DOCTORAL THESIS

Using Artificial Intelligence To Improve The Control Of Prosthetic Legs

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

in the

School of Computer Science and Informatics

December 2018

Declaration of Authorship

I, Pamela HARDAKER, declare that this thesis titled, 'Using Artificial Intelligence To Improve The Control Of Prosthetic Legs' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date: December 2018

"We explore because we are curious, not because we wish to develop grand views of reality or better widgets."

— Brian Cox

DE MONTFORT UNIVERSITY

Abstract

Faculty of Technology
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Doctor of Philosophy

Using Artificial Intelligence To Improve The Control Of Prosthetic Legs

by Pamela HARDAKER

For as long as people have been able to survive limb threatening injuries prostheses have been created. Modern lower limb prostheses are primarily controlled by adjusting the amount of damping in the knee to bend in a suitable manner for walking and running. Often the choice of walking state or running state has to be controlled manually by pressing a button. While this simple tuning strategy can work for many users it can be limiting and there is the tendency that controlling the leg is not intuitive and the wearer has to learn how to use leg.

This thesis examines how this control can be improved using Artificial Intelligence (AI) to allow the system to be tuned for each individual.

A wearable gait lab was developed consisting of a number of sensors attached to the limbs of eight volunteers. The signals from the sensors were analysed and features were extracted from them which were then passed through 2 separate Artificial Neural Networks (ANN). One network attempted to classify whether the wearer was standing still, walking or running. The other network attempted to estimate the wearer's movement speed. A Genetic Algorithm (GA) was used to tune the ANNs parameters for each individual.

The results showed that each individual needed different parameters to tune the features presented to the ANN. It was also found that different features were needed for each of the two problems presented to the ANN.

Two new features are presented which identify the movement states of standing, walking and running and the movement speed of the volunteer. The results suggest that the control of the prosthetic limb can be improved.

Acknowledgements

I would like to thank my supervisors, David Elizondo, Ben Passow and Martin Grootveldt for their support and guidance.

I would also like to thank Annette Baldock, my mother, for believing in me Andy Stevenson, my partner, for feeding me, Thomas Stubington, my nephew, for being my medical advisor and the rest of my family and friends for putting up with me.

Finally I would like to thank all the volunteers without whom this research would not have been possible.

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Abbreviations

AI	**A**rtifical**I**ntelligence
ANN	**A**rtificial **N**eural **N**etwork
CI	**C**omputational **I**ntelligence
DWT	**D**iscreet **W**avelet **T**ransform
EEG	**E**lectro**e**ncephalo**g**ram
EMG	**E**lectro**m**yo**g**raphy
FT	**F**ourier **T**ransform
GA	**G**enetic **A**lgorithm
kHz	**k**ilo**h**ert**z**
kmh	**k**ilo**m**etres per **h**our
ms	**m**illi**s**econds
MSE	**M**ean **S**quare **E**rror
RMSE	**R**oot **M**ean **S**quare **E**rror

Dedicated to my mother, without whom
I would not have had the confidence to do this.

Chapter 1

Introduction

This thesis reports on research conducted on the use of computational intelligence for the improvement of prosthetic limb control. Using a wearable gait lab developed specifically for this research it is demonstrated that movement state and speed can be estimated with a high degree of accuracy using a suitable trained neural network. This network is trained on features extracted from the signals recorded from the wearable gait lab.

1.1 Motivation

At 10.00 am on the morning of 24 March 2004 my life changed in a split second. Somehow, while turning on a ski slope to avoid a beginner, I smashed my femur into the top of my tibia shattering it into several pieces as you can see from the X-ray 1.1. For the next two years I attempted to recover from this having been told I was unlikely to run again and that I may never walk properly. In 2007 I ran 10k in 1 hour and 3 minutes in aid of cancer research. What happened in that split second changed many parts of my life including undertaking this PhD.

For the first few weeks of my recovery the medical staff could not guarantee that they would be able to save my leg and I had two plates and 13 screws holding the bits together as shown in Figure 1.1. During that time I speculated on what might happen if we had to amputate. Having spent many years working with people with disabilities I was fully aware of the amazing developments available that can help. But I was also painfully aware of the challenges and frustrations that have to be dealt with on a daily basis.

I was fortunate, my leg did not have to be amputated. But for the next two years I underwent intensive therapy and rehabilitation to restore as much functionality as possible.

FIGURE 1.1: X-ray of my leg after being fixed with plates and screws

During that rehabilitation I had to learn how to walk again, have my muscles restarted with electric shock and go through enormous pain doing exercises to rebuild muscle and ligament strength. As I carried out these exercises I became painfully aware of how damaged the muscles and ligaments were from both the accident and the surgery I had been through.

Although I could both walk and run it was not without side effects and the way in which my body worked was not the same. So, even though I have not faced amputation I have faced many of the challenges of someone who has had an amputation. I have had to rebuild my body, relearn basic tasks and rethink what I can and can't do with my life.

Top of the ”can't” list was skiing! But top of the ”can” list was make a difference.

Not only are people surviving longer thanks to medical advances but more people are surviving more serious traumas. However, this means that more people are surviving with significant and life changing injuries such as amputations. Along with the medical advances come technological advances which allow more functionality to be implemented in the prosthetic limb.

The technological and social advances of our world also bring higher expectations from all individuals and prosthetic limbs are no exception.

Modern passive micro-processor controlled lower limb prostheses give user's a significant amount of extra functionality when compared with the basic prosthetics of the past. However, the needs and desires of the people using this technology are increasing in line with the improvements in technology.

It is no longer sufficient to just re-create basic walking movements, users want to be able to dance [1, 2], run, ski and do all the things they used to do.

1.2 Problem Statement

The most common method of controlling modern passive micro-processor controlled lower limb prostheses is through adjusting the level of ’damping’ of the mechanical knee joint. This is currently, typically, controlled by a standard algorithm which has been adjusted for the individual. Some models can learn the user’s movements to a certain extent but the primary concern at all times is that the unit will not collapse allowing the user to fall.

Some models also allow the mode of the unit to be altered for different activities such as walking, running, cycling etc. However, in the majority of cases switching between modes is controlled manually either by pressing a remote via button-type controls or by performing a set movement on the leg such as pressing the toe.

In addition to learning these manual controls the user must also learn how to use the leg. There are two main reasons for this. The first is that the loss of the calfe muscle means that other muscles in the thigh and hip need to be used to move the leg forward. The second is that prosthesis must be moved into certain positions for certain actions to happen. For example, before the knee will relax to allow swing through it has to be allowed to completely straighten behind the user.

[3] ”In 2005, 1.6 million people were estimated to be living with limb loss and by 2050, the rate is expected to double to 3.6 million in the United States. (1)”s 295 million population 0.5%

The number of amputees across the world increases every year as medical science successfully saves more lives after life and limb threatening trauma. With this increasing and significant population of amputees it is clear that better control processes are needed.

1.3 Proposed Solution

This work proposed to address this problem by creating a wearable gait lab to capture movement data from volunteers walking and running on a treadmill. This data would then have features extracted from it and be processed using Computational Intelligence (CI) to give accurate near real time control based on users movements. The use of CI would enable the system to learn from the user how they move and improve the accuracy of the system by providing tailored control that can continue to learn.

1.3.1 Previous work from MSc

The PhD work builds on work carried out during my MSc which consisted of:

- Determining a first group of features
- Hand tuning the parameters for both the features and ANN

1.3.2 Work carried out for PhD

The work carried out during the PhD consists of:

- Determing two significantly better features for the task in hand
- Developing and hand writing a GA to tune the parameters
- Improvement to the processing of the data for the ANN
- Introducing a new way of selecting features

It is believed that both the features identified from the data and the format used for the genes within the GA are unique and as far as can be determined, have not been used anywhere else.

1.4 Thesis Structure

This thesis is presented in 6 chapters. Chapter one introduces the work, chapter two gives a full literature review of the current state of the art and chapter three discusses the methodology used. In chapter four the experimental set up is described then in chapters five and six the results and conclusions are presented. A Bibliography is then presented followed by the Appendices.

Appendix A shows the two papers published by the author [4, 5].

- Pamela A. Hardaker, Benjamin N. Passow, and David Elizondo. State detection from electromyographic signals towards the control of prosthetic limbs. 2013 13th UK Workshop on Computational Intelligence, UKCI 2013, pages 120–127, 2013. doi: 10.1109/UKCI.2013.6651296.

- PA Hardaker and BN Passow. Multiple sensor outputs and computational intelligence towards estimating state and speed for control of lower limb prostheses. 2014 14th UK Workshop, 2014. ISSN 2162-7657. doi: 10.1109/UKCI.2014.6930190.

Appendix B details the full ethical review which was conducted and approved by the university. This consisted of:

- Full ethical approval application
- Information sheet for each participant
- Consent form for each participant

Appendices C to H give comprehensive diagrams not shown in the main body of the report.

Chapter 2

Literature Review

In this chapter, the main literature review regarding the developments in amputation, the development of prosthetic legs and the use of sensors and Artificial Intelligence in prosthetic legs is introduced.

2.1 A Brief History of Amputation and Prosthetic Legs

There is evidence that amputations have been performed for thousands of years [6] and that prostheses have been used from early Egyptian times, possibly before. This section outlines the background into amputation methods and prostheses development up to the present time. A brief time line of some important dates is shown in Figure 2.2.

2.1.1 Surgery

Early amputations were performed either to remove a badly damaged limb or to save a person's life via the removal of infection. Initially, such injuries were predominantly caused by accidents, but as the number of casualties from war increased, more subjects suffered such injuries and these injuries became far more serious as the tools of war developed [7, 8]. Furthermore, improvements in medicine gave rise to greater numbers survivable injuries following the initial trauma.

Initial surgical techniques were aimed purely at the speed of amputation and hence the survival of the patient, with tourniquets used to control blood loss. However, without the implementation of sufficient anaesthesial protocols, sterile conditions and suitable after care follow up processes, it was a painful and dangerous procedure with up to 25% fatalities [9]. Even if patients did survive this process, these basic amputation

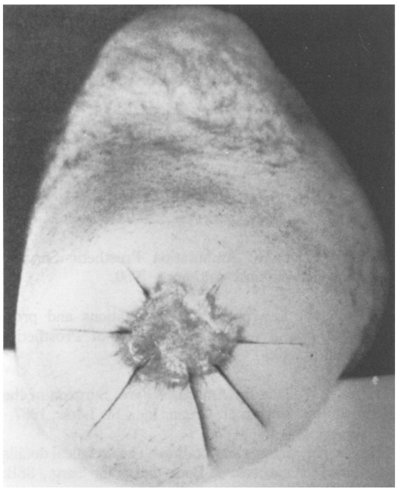


FIGURE 2.1: End result of circular amputation stump treated with postoperative skin traction (Reprinted from An Atlas of Amputations, C.V. Mosby,1949).

methods often did not provide an effective "stump" for the use of prosthetic devices. This was ascribable to the very primitive methods used to diminish the bleeding such as crushing, treating with boiling oil, or cauterisation [7].

However, as human conflicts became more frequent and gave rise to escalated numbers of amputations, surgical techniques improved synchronously and became more straightforward and successful [10]. Indeed, amputations could be performed with consideration of the resulting stump and also the effective use of a prosthetic device. Moreover, many new techniques were developed concomitantly, such as circular amputation strategies (Figure 2.1).

The emphasis of such surgical approaches has now moved on from simple life-saving and basic movement restorations to attempts to restore all elements required for a normal functional life. These approaches have paved the way for the design of more functional and useful prostheses. However, the fact that surgeons often just see their role as only performing the amputation and subsequently healing the skin is discussed in detail by Carlsen et al [11]. Indeed, surgeons may not duly consider exactly how the prosthetic device will be employed in normal day-to-day activities and this may represent a major issue for the patient's outcome. As surgical techniques have improved [12], the chance of the prosthetic succeeding improves and therefore the desire for better prostheses increases.

2.1.1.1 Limb Salvage Versus Amputation

In some situations amputation of a limb is inevitable, whereas in other situations, salvaging the limb represents a clearly viable option. However, there are many situations in which the decision is not completely straightforward and there are many factors that have to be taken into account before the decision to amputate is taken, not least of which is how well the resulting amputation will allow the fitting and use of a suitable prosthetic device [13] .

The relative advantages and disadvantages associated with attempts to salvage or amputate a limb are extremely complex. Indeed, salvage surgeries are often more expensive and are in more demand during the early stages and although it is likely that the patient will have less functionality after surgery than that of a prosthesis user, it is also likely that they will continue to be able to use the restructured leg longer into later life periods for basic movement and weight support [14].

Conversely, amputation offers a cheaper primary solution, with a more rapid recovery time, with the promise of improved functionality arising from an effective prosthesis, at least in the short-term. However, with increasing time, the atrophy of the remaining limb and the problems caused by wearing the prosthetic limb device can render use of the prosthesis less desirable or even impossible.

In such situations, the wearer must utilise a wheelchair or crutches, a development which obviously impacts on their ability to work and maintain a fulfilled life. In some countries, the choice between amputation and limb salvage may be unfairly distorted by the relative levels of payouts from medical or accident insurance companies [14], who often give more substantial amounts for the loss of a limb.

According to Hiatt et al [15], there are many factors that should be taken into account when making final decisions on the amputation and limb-salvage options. Indeed, overall fitness and motivational levels, age and career, together with financial and professional status should be taken into account.

One of the most important factors to consider is exactly how much functionality the prosthesis will provide to wearers and how they will react to use of the prosthesis. Notwithstanding, there is no doubt that an improved functioning and more realistic, functionalised prostheses will improve quality of life outcomes for all amputees.

2.1.1.2 Surgery to Relocate Nerves

Further research work has been conducted regarding movement of the nerves required to operate an electromyographically (EMG)-controlled prostheses where such nerves are not readily accessible, or lie underneath other muscles that diminish their ability to be tracked. In these cases, surgical nerve reinnervation has been employed to relocate the nerves to different areas so that they may be more easily detected [16]. Interestingly, Kuiken et al [17] have pioneered and developed a technique to bring several nerves into a 'grid' located on the chest wall, a process allowing a more elementary placement of EMG sensors. Whilst this provides improved results, it is clearly a very invasive and expensive procedure.

2.1.1.3 Elective Surgery

Prosthesis design has now evolved so far that there are occasions when intact but non-functioning limbs have been removed to allow their replacement with more functional prostheses. Formal experiments for the voluntary amputation of hands have been conducted by Kay et. al and Aszmann et al [18, 19], in which muscles and nerves are moved to render control of the prosthesis more effective. Moreover, Aszmann et al [19] trialled and tracked the prosthetic device alongside the biological hand prior to amputation.

2.1.1.4 Limb Finishing

The manner in which the residual limb is finished can exert a profound outcome on the level of success achieved with the use of a prosthetic device [13]. The purpose of surgical approaches in this case is to both repair the residual limb and also prepare it for mounting a prosthesis and moving this device effectively.

Indeed, the means by which the remaining muscles are finished off has been found to be a factor of much importance. The majority of muscles in the body act in pairs, with both agonist and antagonist components. These components have evolved to be the correct length for the tasks that they are required to perform. During amputation, the length of these muscles is inevitably shortened and the anchor points previously employed no longer exist. In general, there are two techniques employed to complete the muscular surgery: myodesis and myoplasty.

Myodesis is a technique in which muscle or tendon is anchored onto bone using sutures passed through holes drilled into that bone. For example, for a lower limb amputation, the quadriceps muscle (the agonist) may be attached to the front of the remaining femur and the hamstring muscle (the antagonist) to the back, so that they can pull the femur in order to ensure movement of the residual limb [20]..

Myoplasty is a strategy which involves attachment of muscle to muscle, for example, the quadriceps muscle and the hamstring muscle may be attached to each other beneath the femur so that they can pull against each other in order to facilitate movement of the residual limb [21]. In both cases, the muscles have been shortened and no longer act in the same place on the limb, nor with the same forces. As expected, this can exert a considerable impact on the successful use of a prosthesis.

Perhaps the ultimate leg-finishing technique that is now being refined is that of integrating the prosthetic limb directly into the bone known as osseointegration.

Currently, there have been several successful operations performed on animals by Noel Fitzpatrick [22] and a revolutionary research group in Australia known as The Osseointegration Group of Australia are now performing regular osseointegration operations on humans [23].

2.1.2 Prosthetic Leg Development

One of the earliest and well-documented, hinged prosthetic knees was the Paré leg, originally developed by Ambroise Paré in the mid 1500's. This leg incorporated both hinges and a kneeling "pin". In 1696, however, Pieter Adriaans Parézoon Verduyn created a novel leg device with a non-locking lower limb, but whilst this design was innovative, it was not very successful.

In 1816, the Marquis of Anglesey lost his leg in a battle and James Potts designed the "Anglesey Leg" device for him. This leg contained catgut tendons connecting the knee to the foot in order to provide a more realistic flexion. In 1856, this leg was improved by A A Marks who created a more adjustable articulation and control via the addition of knee, ankle and toe movements [8, 24], this leg was named the "American Leg".

The Anglesey or American Leg continued to be in general use until the end of the 1960's. Although some progress was subsequently made with hydraulic knees, this was generally used as a simple replacement for the elasticity within the manual knee. However, the number of amputees created by the two world wars prompted a major requirement for further research into prosthetic control techniques.

The early 1960's [25–27] encompassed the beginning of prosthetists and surgeons working together towards a more successful outcome for patients and in 1970, the International Society for Prosthetics and Orthotics was established.

In general, mechanical limbs continued to be used until the early 1990's, but by this time two of the first real microprocessor-controlled limbs were launched. This development may have been triggered by the introduction of the Disabilities Act in the USA and also the Disability Discrimination Act in the UK. Both these acts required that subjects with disabilities had equivalent access to essential services and facilities. The

Year	Event
1579	Paré leg with "kneeling pin"
1650	Verduyn non locking leg
1800	Anglesey Leg with catgut tendons
1956	SACH foot
1960	Stewart-Vickers hydraulic leg
1963	Prosthetists start to work with surgeons
1967	EMG used for prosthetic hand control
1968	Hensche-Mauch S-N-S hydraulic knee
1970	International Society for Prosthetics & Orthotics inaugurated
1990	Americans with Disabilities Act
1993	Blatchford/Endolite launch Intelligent prosthesis
1995	UK Disability Discrimination Act
1995	Blatchford/Endolite launch Intelligent Prosthesis +
1998	Blatchford/Endolite launch Adaptive Prosthetic Knee
1999	Otto Bock launch C-Leg
2005	Ossur release Rheo Knee
2006	Ossur release Power Knee
2008	Freedom Innovations release Plie Knee
2010	UK Equality Act
2011	Otto Bock launch Genium Leg
2011	Ossur release Power Knee 2
2011	Ossur release Symbionic Leg 3
2012	Blatchford/Endolite launch Orion
2014	Otto Bock launch Genium X3 Leg
2015	Blatchford/Endolite launch Linx

FIGURE 2.2: A time-line of some of the important events in the evolution of prosthetic limbs

Blatchford/Endolite Intelligent prosthesis was introduced in 1993 and this was closely followed by the Intelligent Prosthesis Plus in 1995, the Adaptive Prosthetic Knee in 1998 and the Otto Bock C-Leg in 1999.

Since that time, several other manufacturers have produced improved classes of microprocessor-controlled knees (Figure 2.2). Indeed, each knee device has distinct benefits and the choice is now complicated by this range of advantages.

In Table 2.1 the main types of knee device developed and generated since the early 1990's are shown, together with their relative costs and features.

2.1.3 Current State of the Art of Prosthetic Legs

In the past two years, two new state-of-the-art legs have been launched by the original two leading manufacturers. These are the Otto Bock Genium X3 leg and the Blatchford/Endolite Linx leg.

Knee	**Approx cost**	**Date available**	**Number of selectable movement modes**	**Movement mode selection method**	**Max user weight**
Intelligent Prosthesis (BF)	Superseded	1993	0	-	125kg
Intelligent Prosthesis Plus (BF)	Superseded	1995	0	-	125kg
Adaptive Prosthetic knee (BF)	Superseded	1998	0	-	125kg
C-Leg 4(OB)	£20,000.00	1999	2	Remote	136kg
Rheo Knee (OS)	Superseded	2005	0	-	136kg
Genium (OB)	£50,000.00	2011	5	Remote	150kg
Symbionic Leg 3 (OS)	£40,000.00	2011	0	-	125kg
Orion2 (BF)	Unknown	2012	0	-	125kg
Rheo Knee 3 (OS)	£35,000.00	2014	6	Actions	136kg
Plie knee 3.0 (FI)	Unknown	2014	0	-	125kg
Genium X3 (OB)	£60,000.00	2014	5	Remote	125kg
Linx (BF)	Unknown	2015	0	-	125kg

TABLE 2.1: A basic time-line of some of the most successful micro processor controlled prosthetic limbs

The Genium X3 specification sheet lists the following features:

- Two stance functions
- Five modes of control, operated by a remote fob
- Smartphone app to control the system and switch modes via Bluetooth
- Walk2run function to automatically extend the leg swing for short runs
- Waterproof to 3 metres for up to 60 minutes

The Blatchford/Endolite Linx leg flyer lists the following features:

- Bluetooth connection for ease of programming
- Seven sensors to detect movement
- Linx assist mode to progressively change stiffness at different walking speeds

- Stop and Lock mode to control the knee and ankle flexion during standing
- Controlled ramp descent with knee and ankle braking
- Dynamic stair descent with support on lowering
- Supportive resistance to flexion as soon as the knee stops flexing

The increases in developments witnessed during the last 50 years is almost inconceivable and yet the rate of change is also increasing exponentially. However, the basic principles associated with the requirements remain the same. First and foremost, the leg must be as reliable as possible, but subsequently it must be able to anticipate the user's requirements and replicate as closely as possible user activities.

Whilst all current state-of-the-art limbs function extremely effectively, there remain limitations on their usage. The major one is the manner in which the legs change from one function to another. There are also limitations on the means by which the control systems are adapted to each user's movement patterns and desired activities.

Although the current state-of-the-art of prosthetic limbs is indeed impressive, there is also much current research being undertaken which promises to further improve prosthetic limb control. However, incorporating new research developments into a viable prosthetic limb is costly and time-consuming and must, above all, offer complete reliability to the wearer.

The remainder of this paper will explore these current research areas.

2.2 The Use of Sensors in Prosthetic Limb Control

In order to enable the prosthetic limb to work effectively for the wearer, it is essential for it to 'know' or anticipate what the wearer is doing or about to do.

Many different types of sensors have been used to evaluate and control prosthetic limbs. In general, they are used at two different sites on an amputee, i.e. within or on the prosthesis (known as intrinsic location), or on another part of the body (known as extrinsic location). This difference alone has been researched extensively and Farrell and Herr discuss exactly how to identify optimal sensors and features in their particular contexts [28].

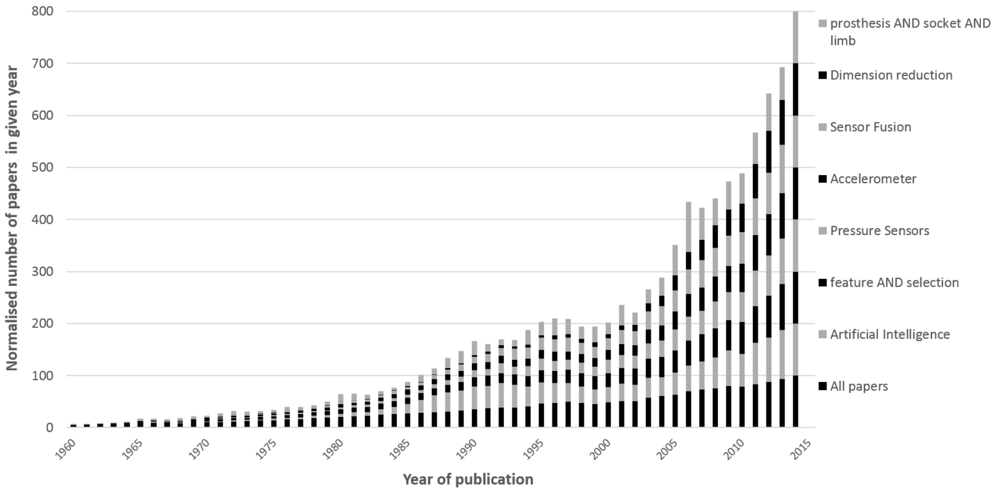


FIGURE 2.3: Normalised representation of the increase in publications in the areas of science relating to the development of prosthetic limbs

Generally, there are 3 means by which such sensors can be employed in the control of prosthetic limbs:

- Measurement of the person's movements for evaluation and comparative purposes.
- Sending control signals to a prosthetic limb directly from the relevant nerve, e.g. monitoring the nerve signals running through a specific muscle and recreating as closely as possible the movement that that muscle would have made [29].
- Sending control signals to a prosthetic limb by evaluating a number of signal outputs and determining an overall 'meaning' from a composite of all the outputs.

In this section the different classes of sensors utilised in prosthetic limb research will be discussed, along with the manner in which they have been employed.

2.2.1 EMG Sensors

Detection of electrical activity within the human body has been studied for many centuries and two particular fields have been developed. These are electrocardiography (ECG), which detects electrical signals within the brain and electromyography (EMG), which detects electrical activity within skeletal muscles. The usefulness of both these fields to predict events within the body has been researched in many areas and ECG has successfully been used to predict the onset of epileptic seizures in humans [30].

This is particularly encouraging in terms of using EMG signals to predict initiation movements within a limb. However, the indicators of an epileptic seizure can occur several minutes, if not hours before the event. However, the events taking place within the leg are required to be predicted in 'real-time' for the effective control of a prosthesis.

The current use of EMG signals is predominantly focused on the identification of a signal and acting on it thereafter. Indeed, simple volitional control of a prosthetic hand using EMG signals was achieved as early as 1967 [31] and they are now being employed to perform complex hand operations in 'real time' [32].

An EMG sensor is attached to the surface of the muscle and as the signals pass through the muscle the EMG sensor detects them and then directs their passage through an attached wire to a detecting unit. It is known that the residual limb of an amputee can continue to provide signals to the missing portion of the limb and Huang et al [33] have discussed the challenges presented by these processes. It is also known that the signals that reach the surface-mounted EMG sensor have then to pass through other muscles, tissues and bone and this may exert a detrimental effect upon signal recognition and processing [34].

EMG sensors are often used in an attempt to replicate the exact movement demanded by the brain [35] and Lee and Saridis [36] constructed an EMG signal pattern recognition system for the 'real-time' control of a prosthetic arm through the precise identification of motion and speed commands.

They can also be used to distinguish movement modes for lower limb prostheses [33] and volitional control of the quadriceps and hamstring muscles has been examined by Ha et al [37], who employed the EMG signals to directly interpret the user's intent to flex or extend the knee with some success. However, Hargrove et al [38] investigated the use of residual EMG signals in order to control the lower limb whilst recipients were seated.

Pilarski et al [39] have used EMG signals to provide online real-time control and confirming the methodology's applicability to control the limb in real-time. Hargrove et al [40] found that EMG signals arising from re-innervated nerves improved the control of the limb over the mechanical limb sensors alone.

The next step on from direct, real-time control is the ability to predict a movement that the wearer is about to make before it can be made. Chen et al [41] utilised a fusion of sensors in order to recognise and in some cases, predict transitions between activities such as walking and stair and ramp ascents. However, Farmer et al [42] used a non-linear autoregressive model in order to map the recorded EMG signals from an amputee's leg and together with kinematics from the amputee's prosthesis to estimate ankle angle. The success of this research work suggested that this approach could be employed for direct control.

Further research work performed using EMG signals includes that of Woodford and Price [43], who employed EMG feedback to assist patients to recover movement following a stroke. This technique may also be beneficial to prosthesis users with muscles which may have suffered a similar trauma or atrophy.

The EMG sensor therefore holds much promise for application to prosthetic limbs and it has been employed to great effect with upper limb prostheses. However, although much research has been carried out on its use with lower limb prostheses, to date there has been no commercial usage of such a sensor system. The potential offered by this research suggests that this is an area that could indeed be further developed.

2.2.2 Pressure Sensors

Simple pressure sensors have been employed for many years to assist the control of lower limb prostheses. In general, such sensors have been inserted in one of two places, the sole of the shoe or in the socket of the prosthesis located beneath the residual limb.

From testing of the internal pressure within the socket [44] to being a component of a multi-sensor system in order to detect phase gait [45–47], advancements and refinements in the application of pressure sensors has revealed a range of possibilities for their use.

Some researchers, such as Wang et al [48] and Huang et al [49], employ signals from the sensor to identify individual actions within the walking gait, such as 'heel-down' or 'toe-off', which indicates the start and end of the stance and swing phases respectively (Figure 5). Although Novak et al [50] use wearable inertial measurement units and pressure-sensitive insoles to detect gait initiation and termination.

Chen et al [41] have employed pressure sensors to determine if the user is sitting or standing. Furthermore. Huang et al [45] have found that the composite fusion of EMG and load cell (pressure sensor) signals is more effective than EMG alone. These investigators also experimented with the concept of using different classifiers, which depended on the current gait phase.

Pressure sensors in one form or another are already incorporated into many commercially-available prosthetic legs. Moreover, there is potential for information gathered from these sensors to be used more extensively in terms of both control and predictive capacities and also to be used as a component of fused sensor data.

2.2.3 Electric Goniometer Sensors

A goniometer in its simplest form measures the angle between two items and this concept originated from early Greek times [51]. Indeed, electronic goniometers have been used for many decades in the field of prosthetic limbs. In 1977 Lyman et al [52] used goniometers to check and monitor the position of a prosthetic arm which had been EMG-predicted.

Within the field of prosthetic legs, the goniometer is typically used to measure the angle between the lower and upper leg at the knee and also between the lower leg and the foot at the ankle.

Goniometers can now be produced very cheaply from readily available components [53] and can also be bought in a ready-constructed form and are generally used in two ways, in the field of prosthetic limb control and in the field of gait analysis.

Additionally, they can be employed to detect the current angle of a joint in order to feed into a control algorithm for that or other joints [37, 54]. Furthermore, they can be used to verify that the desired angle calculated from an EMG signal is correct [55].

2.2.4 Accelerometers

Accelerometers can measure movement in three planes and the first device of this kind was developed around 1923 by McCollum and Peters [56, 57]. Such devices have now developed to become extremely light and wearable sensors.

They were in use for many years before being incorporated into prosthetic limbs. For example, Preece et al [58] extracted the movements of the wearer in order to analyse the level of movement made during a given time period. This information was then used to test lifestyles in conjunction with corresponding investigations focused on fitness and obesity.

Within the field of prosthetics, a variety of approaches have been employed. In some cases, accelerometers have been used to confirm the movement of the user whilst wearing an EMG sensor such as that demonstrated by Scheme et et al [59] and Fougner et al [60]. The purpose of this is to increase the accuracy of the EMG reading, or alternatively to counteract potential movement of the EMG sensor during use.

Other researchers combine these devices with pressure-sensitive insoles in order to detect simple gait initiation and termination activities, such as 'heel down' and 'toe off′ criteria [46, 50], or in conjunction with EMG sensors for both intrinsic and extrinsic control as noted above [28].

They have also been used to determine the stance of the wearer in order to assist with control of the exoskeletal martix [61].

Accelerometers have now reached the mass market and have been incorporated into smartphones and smartwatches, for example. Intriguingly, Guiry et al [47] used these sensors to determine whether or not an individual is walking, climbing stairs, standing, sitting or bicycling.

2.3 Sensor Fusion

As different sensors have developed and the techniques available for interpreting the signals have improved, work on the use of fusions of such sensors. As can be seen from the number of papers produced on this subject Figure 2.3, the use of this technique has dramatically increased over the last few years.

Both Hong et al [44] and Huang et al [45] compare the effectiveness of a combination strategy favourably over the use of EMG sensors alone, located in the socket of the prosthesis. Interestingly, Young et al [62] explored the use of EMG sensors together with mechanical ones attached to the prosthetic device for the purpose of intention recognition within a powered prosthesis.

Pradhan and Prabhakaran [63] however, investigated the identification of movements from a fusion of sensors using a clustering strategy and concluded that fusion processes can be carried at three different levels, i.e., at data, feature and decision levels.

It is virtually impossible to know what techniques are used within many commercially-available prostheses as this information is closely guarded. However, there can be little doubt that using a fusion of sensors offers great potential for future developments.

2.3.1 Wearable Gait Laboratories

When attempting to assess a person's walking mode, there are, of course, inevitable problems caused by the observation process itself. Indeed, many gait laboratories only allow patients to walk a short distance and also require a high level of expensive equipment which has to be set-up and calibrated in each case. There are also inherent problems with the monitoring of gait on a treadmill, which is caused by the unnatural movement mode of the treadmill itself [4, 5]

The possibility of a wearable gait laboratory is considered and discussed in detail by Najafi et al [64] and Chelius et al [65] successfully used a wearable sensor network to record measurements on a runner during an extreme race. + Whilst there is the possibility of a loss of the high resolution of data and also the introduction of at least some noise, such a wearable solution will provide substantial benefits as far larger quantities of data are gathered in real-life situations rather than those acquired on treadmills or in laboratories. These data can then be used either for the control of the limb directly in real-time or be recorded and employed to improve training of the limb.

2.3.2 Summary

The development of smaller and more accurate sensors has allowed prosthetic limbs to become far more responsive, as reviewed here. These sensors have been combined with smaller, faster and more responsive microprocessors and further systems to yield a much clearer 'picture' of exactly what movements an individual is performing which has, in turn, permitted the development of more responsive control strategies. From the patterns created by an individual and pairs and groups of collaborating sensors, it is indeed possible that movements could be predicted at some point in the near future.

2.4 Data Processing

The signals received from the sensors contain a vast amount of raw data which has to be interpreted. Typically, this process will consist of some form of pre-processing to smooth and correct the signal, followed by the extraction of relevant features which will facilitate identification of the movement being performed by the wearer.

Once extracted, these features can be employed to determine the wearer's movements by classifying them and seeking patterns.

2.4.1 Preprocessing

The signals received from the sensors represent what the user is doing in several ways. However, they are prone to interference and noise that requires removal or reduction as far as is practicable. This is achieved via the pre-processing of signals generated from the sensors.

One of the aims of preprocessing is to alleviate the inherent deviations found within most sensors. These include:

- Sensitivity errors, where the sensitivity of the sensor differs from the pre-specified value;
- Saturation errors, where the signal intensity exceeds the limits of the sensor;
- Offset errors, in which the output signal is not zero when the measured property is;
- Non-linearity errors, where the sensitivity of the sensor modifies throughout its range;
- Dynamic errors caused by rapid changes of the measured signal over time;
- Drift errors, where the output signal slowly changes independently of the measured property;
- Noise, caused by deviations of the signal over time;
- Hysteresis errors, where the signal has actually reversed, but the sensor takes time to respond, a process thus creating a time lag;
- Digitalization errors caused by the simple process of gathering a digital value for an analogue signal;

These deviations can be overcome to some extent by the use of a calibration strategy, or alternatively by using filtering in order to remove errors such as those arising from noise. Sometimes a simple method can be used, such as basic averaging over the last three samples, or removing any signal below a certain minimal level [4, 5]. Other methods that have been employed are band-pass filters [66, 67], low pass filters [53], rectification and down sampling [42], Butterworth filters [42, 68], notch filters [42] and others.

2.4.2 Feature Extraction

Once the signals have been processed, it is necessary to extract the relevant features that distinguish one state from another. Park and Lee [69] describe this as the ”main kernel of classification systems and is essential to the motion command identification”. These researchers also highlight the fact that it is difficult for a single feature to reflect the overall state of the signal. Thus, several different features are required.

There are two major approaches in which features can be extracted from signals. The first is by using automatic methods such as Fourier Transforms (FTs) and Discrete Wavelets (DWTs). Whereas the second functions by the observation of signals that occur during certain known events such as heel down/toe off, or switching from walking to running. Most reports agree that the extraction of data from this signal in a timely fashion represents one of the most difficult aspects of this process.

2.4.3 Window Size

One of the major issues to be considered in both signal processing and feature extraction is the window size or number of samples used. If this window is too small, an insufficient number of signal samples will be collected, thus yielding inaccurate results and hence often it is determined that a larger window is preferable in order to balance the effects of classification error and controller delay [70].

However, if too large a window is employed, then there is potential for the result to arrive too late in order for it to provide a timely outcome. The optimal control delay period was estimated by Farrell and Weir [71] to be between 100 and 125 ms for their purposes. Therefore, at a sampling rate of 1 KHz, approximately 100 samples can be used, but if the sampling rate is reduced to 100 Hz, however, then only 10 samples will be available and this may exert a significant effect on the results achieved.

2.4.4 Automatic Features

Automatic features allow information to be extracted from individual signals using known or established formulae and principles such as Fourier Transformation.

Much research work has been conducted using differing automatic feature extraction methods. Indeed, Moghim and Corne [30] analysed an existing electroencephalogram (EEG) dataset documenting epileptic seizures gathered over a 24 hour period to extract features such as the mean signal energy and the accumulated energy.

Other automatic processing methods include observation of the stationarity of the signal [72]. This work also utilised the mean absolute, the difference absolute mean and the difference absolute standard deviation values. EMG signals are not stationary and this approach attempts to introduce stationarity; use of a combination of time-dependent and stationary features improved classification.

Standard deviation, kurtosis and median power frequency values were extracted by Johnson and Sensinger [73] and then compared when zero-order or first-order control was used. First-order control was found to be more effective in this context.

Passow et al [74] took the process one step further and employed a genetic algorithm (GA) analysis strategy to automatically determine the correct features to use. This work correlated the major peaks within a certain frequency spectrum with the speed of the rotor.

Pattern recognition control has been shown to outperform conventional myoelectric control using amplitude measurements in upper limb patients with targeted muscle re-innervation by Hargrove et al [16]. In this instance, the control system consisted of time-domain features, together with auto-regressive coefficients classified by a linear discriminant analysis classifier system.

Further automatic features extracted included:

- Mel-Frequency Cepstral Coefficients (MFCCs) [75–78]
- Arithmetic and Root Quadratic Means [28, 77]
- Linear Regression [77, 79]
- Root Mean Square [28, 80, 81]
- Zero Crossings [28, 29, 82]
- Slope Sign Changes [28, 62, 83]
- Fourier Transformation [63, 74]

2.4.5 Observed Features

Automatic features can provide much information regarding the behaviour of individual signals. However, the observation of one or more signals during a specific event can provide more pertinent information for the purpose of prosthetic limb control. Examples of such events are again heel down and toe off.

Zhang et al [84] used the number of zero-crossings and the number of slope sign changes for the real-time prediction of the intention to sit or stand, whilst in Hardaker et al [4, 5], the distance between clusters of EMG signals and the cross-over points of two pressure sensors were utilised to determine whether the wearer was running or walking.

2.4.6 Dimension Reduction

As an increasing number of more useful features residing within the signals are identified, further problems arise, i.e. how long it takes to process this critical information.

This problem occurs both off-line when training and on-line for the purpose of real-time control. The obvious solution is to reduce the number of features by choosing only those that are appropriate.

Some automatic methods have been developed to achieve this and these include those of Geiger et al [77], who employ a ”wrapper” based feature selection technique [85] in order to reduce the feature set, a development which assists with the evaluation of sub-sets of the features and also evaluate how selected features interact with each other.

Determining the ideal features to be used in each case is also discussed by Farrell et al [28]. The method described in this work uses both EMG and internal sensors for intrinsic and extrinsic control whilst participants walk on different types of terrain. The novelty of this system is that it considers pairing features, using different classifiers for different parts and windows located at important points in the gait cycle.

Clearly, reductions in the number of features will, unfortunately give rise to the loss of at least some information. However, if these removed data arise from redundant features (or those which contain an element of duplication with other features), then this loss may be considered unimportant [86].

2.4.7 Training Methods - Issues

Once the relevant features have been selected from the available dataset(s), they can then be used to train and work with a classifier. Techniques such as fuzzy mapping functions [69], artificial neural networks [4, 5, 34] and majority voting have all been explored [41, 83, 87, 88].

However, Lock et al and Chicoine et al [82, 89] both discuss the fact that pattern recognition techniques are effective for prosthesis control, but the usual training method of screen-guided training, in which the screen counts down and the user moves according to an on-screen prompt is not effective. Therefore, instead they use prosthesis-guided training to prompt the user when to move by performing the function that will be carried out with the prosthesis and then requesting the user to ’mirror’ this process.

2.4.8 Noise and Uncertainty Filtering and Modelling

With all sensors, there is, of course, an element of noise and uncertainty, particularly where the sensors are worn on the body. This may be caused by movement of the recipient, interference from other electrical equipment in the vicinity, or an inherent uncertainty within the sensor itself.

However, it is possible to alleviate the effects of such noise using filtering and smoothing strategies, as outlined above in section 2.4.1. It has also been found that using a fusion of sensors facilitates reductions of the effects of such noise and uncertainty [90].

2.4.9 Modelling and Decision Making

Many different methods of modelling data received from sensors have been investigated, along with many methods of decision making for the control of prosthetic limbs.

Indeed, the simplest form of decision making is to place EMG sensors on the relevant nerve within the residual limb and then move the relevant part of the prosthetic. This technique has been used extensively for upper limb control [16] and has been found to be very effective when precise movements are required to be engendered.

However, for both upper and lower limb control, such precise interpretations of the signals are not always facile or indeed necessary. In some cases, it may be difficult to isolate the correct nerve and noise will cause the signal to be interrupted or lost. Pattern recognition has therefore been investigated by many researchers in order to determine whether the collation and analysis of multiple signals can indeed improve recognition.

Young et al [29] compared an amplitude-based combination of myoelectric signals with sequential pattern recognition control (i.e. a single moving joint) and also simultaneous pattern recognition control (i.e. several joints moving simultaneously) in which each movement was trained as a separate task. Where multiple movements were required the simultaneous pattern recognition control proved more effective.

Other common types of classifier that investigators have researched are:

- Bayes Classifier [39]
- Support Vector Machine (SVM) [77]
- First-Order Markov [91]

Kurzynski [91] compared a first-order Markov strategy modelled to five contextual classifiers:

- Bayes with Markov
- Fuzzy logic
- Fuzzified feature and decision spaces

- Neural networks
- Dempster-Shafer theory.

The first-order Markov model was found to be superior to the other models explored.

2.4.10 Artificial Neural Networks (ANNs)

An artificial neural network is a method of making decisions based on the biological neural network found in the brain. Information is passed through a series of connection units, known as neurons, as coded signals. The neurons are arranged in layers and as the signals pass through different reactions are triggered in the neurons to produce a result. Through this process the network can "learn". A fuller definition of and ANN is provided in Section 3.3.5.

Liu et al [92] used an ANNs model to predict muscle forces from EMG signals. In this study, the muscle force was measured and compared with predictions made by the ANNs from EMG signals from sensors embedded within the legs of animals and it was found that the ANNs approach could indeed successfully capture essential features of the EMG force relationships of the dynamically contracting muscle.

The inputs from an EMG sensor were passed through a dynamic recurrent neural network (DRNN) by Cheron et al [93] in order to control all three sections of a virtual limb in a computer-based muscle. Indeed, Galajdová et al [94] predicted gait parameters from EMG signals.

This suggests that an ANNs strategy can be used to predict muscle forces based on EMG signals.

2.5 Control

The classified data acquired from the features extracted from the sensor signals can be used to pass control data to the prosthetic limb.

Some of the research for these control strategies has come from other areas such as robots [95] and exoskeletal matrices [96] and Rosen et al [97] investigated a powered exoskeleton to augment or support real control.

The aim of such control strategies is essentially 100% reliability as lack of confidence in a prosthetic limb is one of the most common reasons for abandoning its use. The effect of recognition errors were previously examined by Zhange et al [98] in the context of which component of the walking gait the error actually occurs in. For this purpose, these researchers introduced intentional errors to determine if they exerted an effect on users and concluded that not all such errors cause instability.

The Plymouth Hand project [34, 66, 99] has extensively researched the use of an EMG signal to control a prosthetic hand and the investigators involved describe how a single EMG signal is gathered and passed through a series of filters in order to remove noise arising from mains electricity. These filtered signals where then fed into a neural network which had been trained to recognise a series of positions for the hand to move into; this proved successful, at least for some forms of basic control.

Some control systems have been developed for specific tasks and the experiments performed by Villagaray-carski and Herr [2] permitted a below-knee amputee to dance again.

Artificial intelligence has been employed to enhance control by the recognition of patterns [100] and in this study an arm with 4 movable joints (shoulder, wrist, elbow and fingers) was trained. Normally, the user would have to manually cycle between these joints, but this investigation explored the use of adaptive switching in order to move to the next appropriate joint based on previously acquired information. The choice is then made using General Value Functions (GVFs) to generate Temporally-extended predictions regarding a signal of interest that have been applied for sequentially acquiring real-time anticipatory knowledge in relation to human-machine interactions. This learning process appears to be situation-specific and is achieved by the repetition of pre-set tasks through a series of set motions. A decreased number of switches were required to move from one joint to another, a process decreasing both the time involved and frustration level of the user. Having to click through too many settings is one of the major reasons that amputees terminate the use of prostheses

The most radical control systems developed thus far are described as "bionic reconstruction" by Professor Oskar Aszmann [18, 19, 101], a surgeon who has performed amputations pre-selected by patients since the prosthetic hand involved offered greater functionality than their non-functional biological ones.

2.6 Feedback and Reinforcement

The final stage of the control system is feeding back the effectiveness of the control system, either for evaluation or to potentially reinforce the 'learning' of the system.

Intriguingly, Guiry [47] employed smartphone and smartwatch sensors in order to determine whether someone is walking, climbing stairs, standing, sitting or biking. However, although this is not within the context of prosthetic limb control, it reveals great potential for being incorporated into a prosthetic limb control system at a future date.

Depth-sensing is used with the Kinect by Krausz [102] with the aim of improving stair climbing. While this would not be useful in a 'real-world' setting, it may offer advantages within a training environment.

Parker et al [103] have developed a system that learns when an object is close and therefore informs the user with vibrotactile feedback. Such a system could indeed be of value in providing the prosthetic limb wearer with an increased level of awareness regarding their surroundings, together with the position of the floor.

Reinforcement is an extension to feedback and involves the use of such information being fed back to reinforce the 'learning' of the system. Indeed, Pilarski et al [104] have developed such a system in which the arm 'learns' from feedback it receives from an EMG sensor.

This is a novel and developing area, which promises further advancements in the field of prosthetics in the near future.

2.7 Conclusions

Although prosthetic limbs in one form or another have existed for many millennia, their functionality has remained very basic and with very little development until the middle of the 20th century. Since that time, substantial improvements in both materials and microprocessors have allowed huge leaps forward in the functionality of commercially-available prosthetic limbs, which are now very effective at recreating more of the day-to-day activities required by their wearers.

However, there remain limitations to tuning the functionality of these limbs and the current research areas highlighted in this report promise further future developments.

Artificial intelligence offers the possibility of determining precisely what a person is doing and can serve to adjust the control accordingly on a real-time basis. This strategy also offers much potential for adjustments to the system concerned in order to suit recipients on an ongoing basis.

In this chapter an introduction has been given to the current state of the art of the development of prosthetic legs.

In the next chapter the methodology used for this research will be discussed.

Chapter 3

Methodology

This chapter introduces the methods and techniques used for the thesis and the method by which the thesis was tested.

3.1 Introduction

The majority of micro processor powered prosthetic limbs use a standard, straightforward control strategy.

There are only two parameters that can be controlled, the amount of resistance used to control the speed at which the knee swings and the angle to which the knee is allowed to move.

Figure 3.1 shows the basic walking gait. At different times throughout the walking step differing angle and resistance values are required. For example in the stance phase the resistance needs to be high and the angle limited to prevent the knee collapsing. However, in the swing phase the resistance needs to be low to allow the knee to swing through but the angle needs to be high enough to hold the foot up to prevent it from hitting the ground.

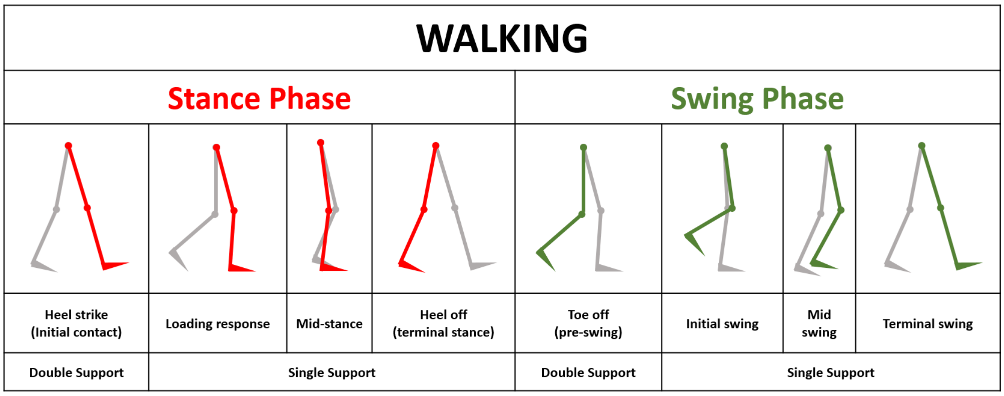


FIGURE 3.1: Illustration of the Walking Gait

In a biological leg these parameters are controlled by the muscles which both dampen the movement on swing through and stiffen the knee on stance. However, in a prosthetic limb this control can only be provided by adjusting some form of resistance such as magnetic or hydraulic fluids.

During the stance phase the resistance is increased as weight is applied to support the wearer then, when a certain angle is reached, the resistance is increased further to stiffen the joint and support their entire weight. During the swing phase the resistance is reduced so that the leg is allowed to move more freely until the leg reaches the end of the swing when the resistance is increased again to slow the leg in preparation for the stance phase.

For this system to work the wearer has to learn to walk with the prosthesis in a certain way. For example, the leg will not leave stance phase until it is fully extended behind the wearer. This is not always a natural movement.

However, the leg must also be as reliable as possible to minimise the risk that the user will either be knocked off balance by an over stiffened knee on swing through or that the knee will collapse when the wearer transitions onto the leg to weight bear.

When a new user starts to wear a prosthetic leg he/she begins with a standard control strategy which is then tailored to their needs through adjustment by a prosthetist [105]. The user has little or no control over the final adjustment.

In order to carry out different activities such as running, cycling or playing golf, a new control strategy needs to be defined and the user can only change between these strategies by making a conscious choice. This is indicated either through a remote control or by carrying out a specific task with the leg such as tapping the toe three times.

These types of control strategies and selection methods are neither natural nor intuitive and the user actually has to learn how to "use" the prosthetic leg. The work described in this chapter outlines how the leg could be made to learn the user's movements.

As previously described in Section 1.3.1, this work builds on work completed during my MSc. A system was developed to gather data from the user. Features were extracted from this data and used to build an ANN to classify the user's movement mode and speed.

The system was then tested on a number of users and in each case a GA was used to determine what parameters should be used for the feature extraction and which features should be used. The process used is shown in Figure 3.2.

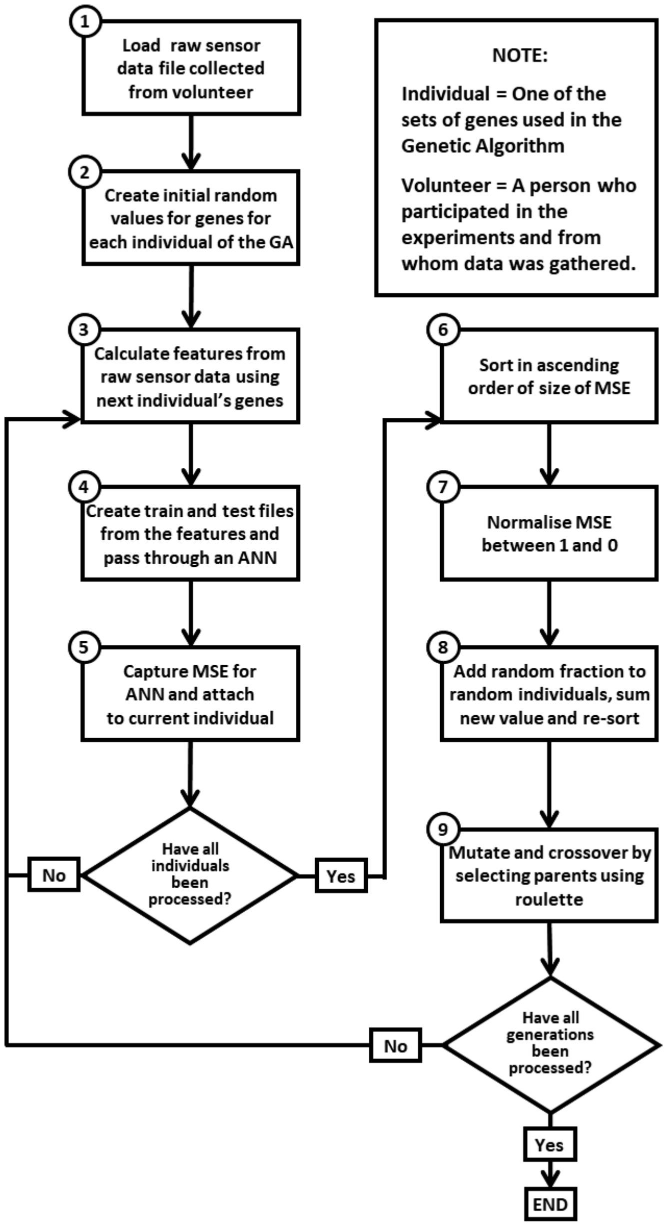


FIGURE 3.2: The flow of data through the system

3.2 Gathering Data From the Wearer

In order for a prosthetic leg to learn how the user walks, runs, cycles or carries out any other activity information must be gathered from that user during such activities.

The walking gait has been studied for centuries. From the drawings of Leonardo da Vinci (1452–1519) to publications such as Nouvelle Mécanique des mouvements de l'homme et des animaux (1798) by Paul-Joseph Barthez [106] and Théorie de la démarche (1833) Honoré de Balzac [107, 108] the way in which our body moves has fascinated us.

Emil du Bois-Reymond [109] and Carlo Matteucci [110] [111] took this study further and reasearched ways to record the nerve activity being used to control the limbs.

These recorded signals have been used for many years for analysis of the body in a variety of different ways.

Having analysed the walking gait as shown in Figure 3.1 a harness of sensors was designed to gather signals from the user as outlined in Section 4.

The harness consisted of:

- One EMG Sensor
- Six pressure sensors, one under the heel, toe and ball of each foot
- Four accelerometers, one on the thigh and calf of each leg
- Wheel Sensor

Features extracted from the data gathered were used to classify the wearers movements.

3.3 Signal Processing

Raw signals from the sensors would not be sufficient to classify the wearer's movements alone and so signal processing was used to allow features to be extracted.

3.3.1 Pre-Processing the EMG Signal

Before features were extracted from the raw EMG signal (shown in Figure 3.3) basic pre-processing was carried out. This consisted of:

- Translate the EMG signal into its absolute
- Remove any EMG signal below a pre-determined threshold of n to eliminate the background signal

This resulted in a series of spikes shown in Figure 3.4 and its comparison with the original signal is shown in Figure 3.5. Features could then be extracted from these spikes.

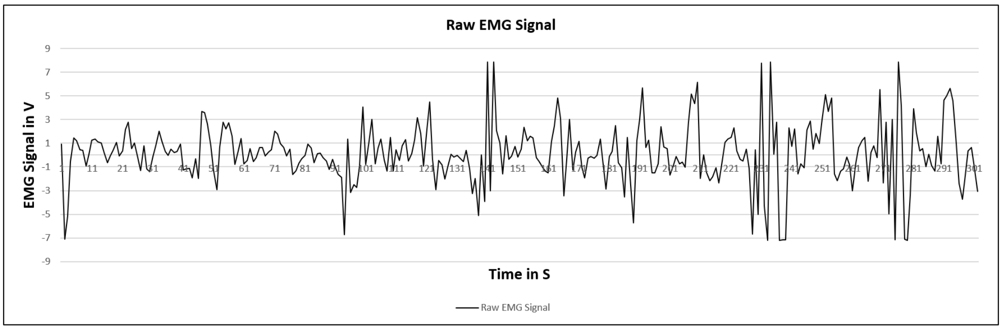


FIGURE 3.3: The raw EMG signal

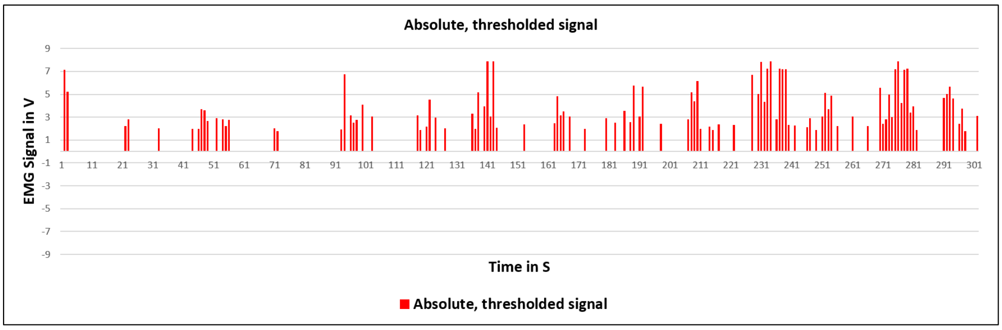


FIGURE 3.4: The absolute EMG signal thresholded above the spike value

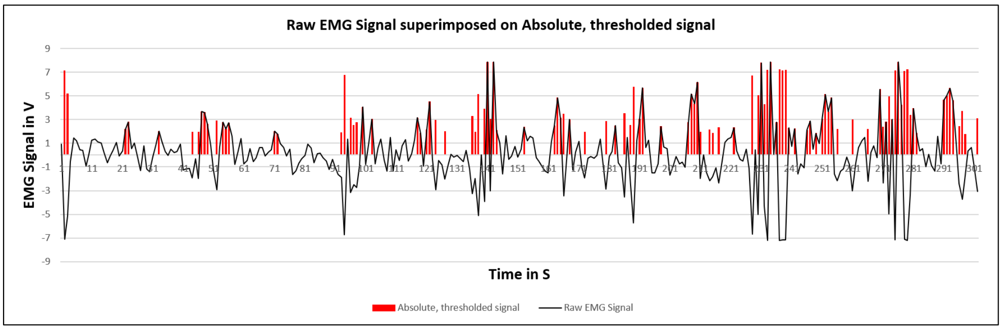


FIGURE 3.5: The raw EMG signal superimposed onto the spikes

3.3.2 Feature Extraction

A number of features were identified that could help to classify the wearer's speed and movement as follows:

1. The raw EMG signal
2. The width of the gap between the last two spikes of the EMG signal was recorded and maintained as a value until the next spike gap was recorded or until a threshold was reached.
3. The width of the gap between the last two clusters Clusters A and B of the EMG spikes was recorded and maintained as a value until the next cluster ended (shown in Figure 3.6).
4. The width of the last cluster of EMG spikes was recorded and maintained as a value until the next cluster started or until a threshold was reached (shown in Figure 3.6).
5. The maximum sample value of the EMG signal over the last x samples (shown in Figure 3.6 and Equation 3.1).

$$s_i = Maximum(EMG_{i-x} : EMG_i) \tag{3.1}$$

6. The average value of the EMG signal over the last x samples (shown in Figure 3.6 and Equation 3.2).

$$s_i = \frac{1}{x}\sum_{i-x}^{i} EMG \tag{3.2}$$

7. The heel and toe pressure sensor crossover point was recorded when it occurred and maintained as a value until the next crossover point occurred (as described in Section 3.3.3).
8. The difference between the current accelerometer reading and the previous reading was calculated to give a rate of change or jerk (as described in Section 3.3.4).

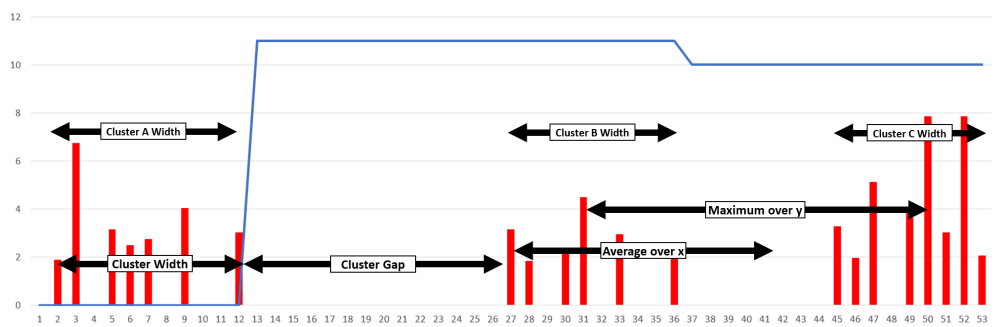


FIGURE 3.6: The Cluster Width, Cluster Gap, Average and Maximum features extracted from the EMG spikes with the change over in speed from 0 to 12 km/h

3.3.3 Pressure Sensor Feature

Three pressure sensors were placed within the shoe of the user as shown in Figure 3.7.

FIGURE 3.7: Position of pressure sensors

The pressure sensors used record values between 0 and 700. This is an arbitrary value with no units and will vary depending upon the shoe, the person, the ground, how the force is distributed etc. The actual value recorded by the pressure sensor is not relevant, what is relevant is the relative value of one pressure sensor reading both from two different sensors at the same time and from one pressure sensor at two different times.

As a result of the analysis of the data sets in this work, a second close relationship was found between the changeover from heel to toe pressure and whether or not a subject was walking or running.

As can be seen from Figure 3.8, the change in pressure on the heel and toe sensors follows this sequence:

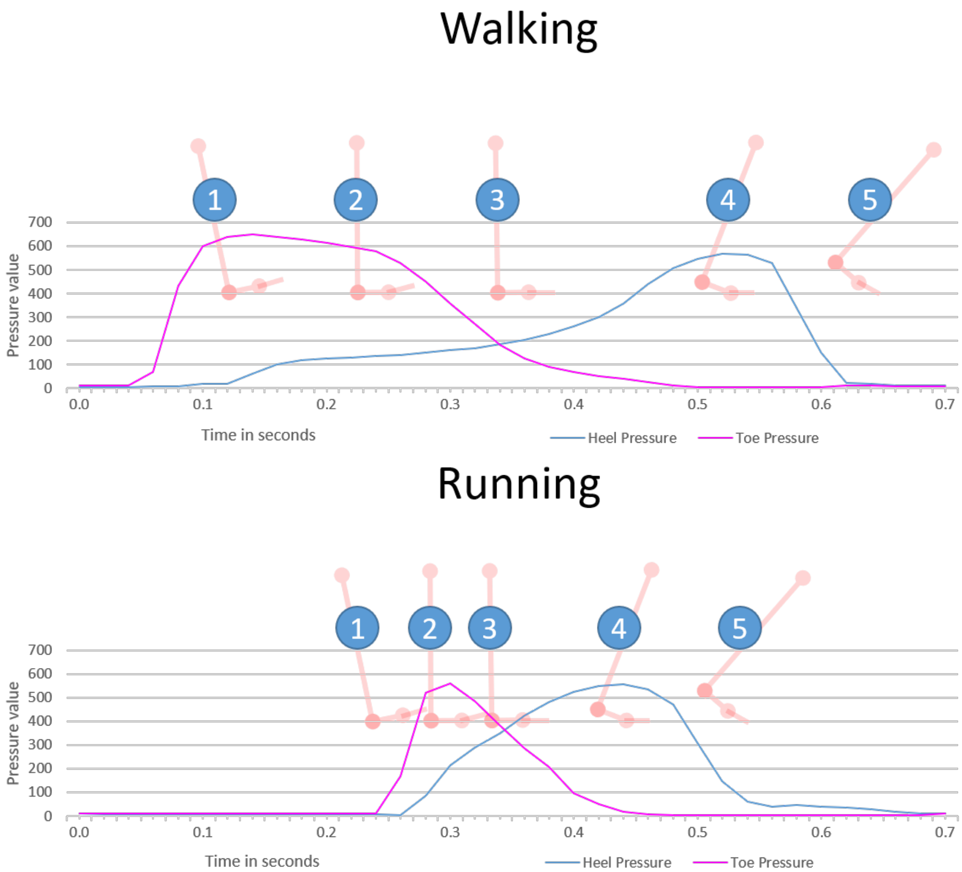


FIGURE 3.8: The heel and toe pressure crossover points when walking and running

1. The "Heel Down" event causes a sudden spike in heel pressure (the pink line) as the heel strikes the floor and reaches its peak pressure
2. As the foot rolls forward the heel pressure starts to decrease and the toe pressure (blue line) starts to increase as pressure is applied by the toe inside the shoe
3. When the foot is flat on the floor the toe and heel pressure values cross over
4. As the foot rolls further forward the heel pressure drops to zero as the foot starts to lift out of the shoe and the toe pressure increases to a peak
5. At the "Toe Off" event the toe pressure drops suddenly away

Figure 3.8 shows this feature for both walking and running. As can be seen when walking the crossover point occurs when the pressure sensors are registering a value in the region of 200 whereas when running this value is in the region of 400. This change in crossover value represents a clear feature that can be used to make a connection with the movement state of walking or running.

Figure 3.9 shows the results of this feature as a black dotted line with the actual recorded movement states of standing (0), walking (1) and running (2) shown in solid black.

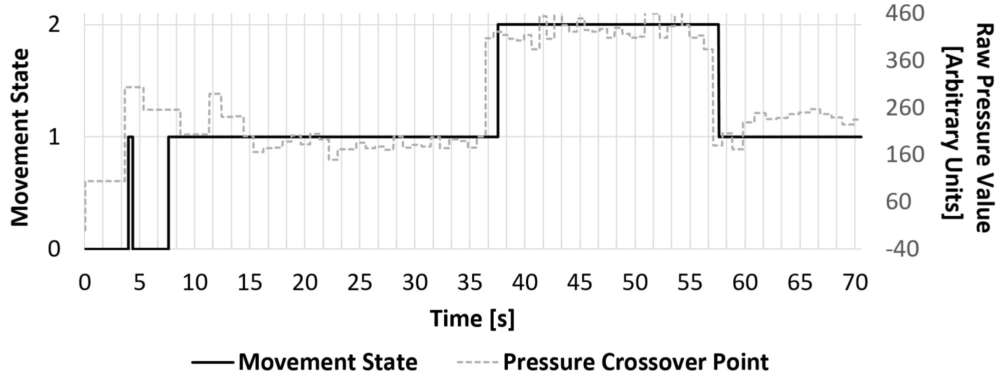


FIGURE 3.9: The heel and toe pressure crossover feature shown as a grey dotted line compared with the actual movement state of standing (0), walking (1) and running (2) shown in black.

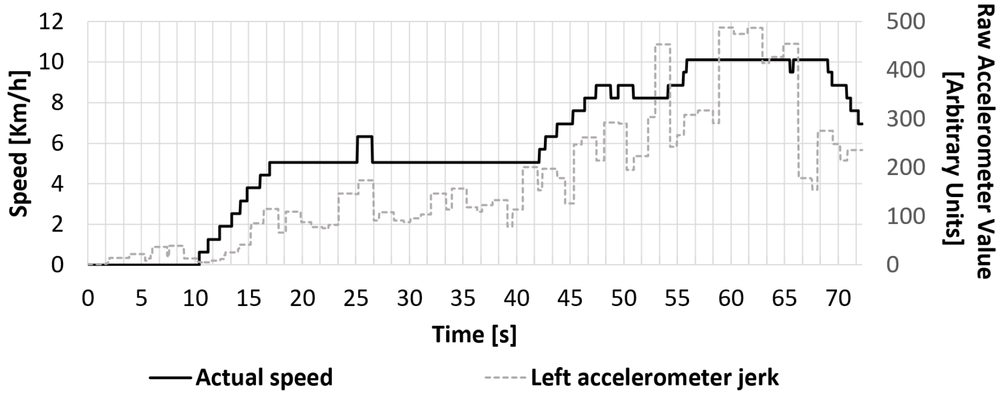


FIGURE 3.10: Comparison of speed against the jerk feature from the accelerometers

3.3.4 Accelerometer Jerk Feature

The "jerk" of the accelerometers was calculated by subtracting the current accelerometer reading from the previous one and then averaging over n readings. It was found that this gave an approximation of the speed at which the subject was walking or running. Figure 3.10 shows this feature as a grey dotted line compared against the speed recorded by the wheel sensor after smoothing by averaging over the last n samples as determined by the GA. As can be seen there is a correlation between these two traces.

3.3.5 Artificial Neural Networks

Following the completion of this literature review and the success of the previous work it became clear that no previous work has been done to determine if each individual needs different parameters for the settings of their prosthetic limb. This thesis therefore explores use of a GA to tune the parameters of the ANN and gather further data to test this thesis.

Following the success of the ANN in the previous work [4, 5], it was determined that this should continue to be used in this work. The reasons for this were:

- The tasks being attempted include classification and regression, both of which work well with ANN's
- The purpose of this work was to improve on the previous work using a GA to optimise the parameters and compare the results for different subjects and so an ANN needed to be used again
- An ANN has better potential of dynamically learning and improving in the future if the subject wishes to change their profile

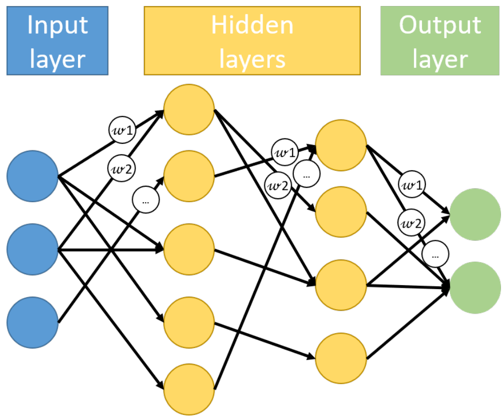


FIGURE 3.11: The basic components of an artificial neural network

An artificial neural network (ANN) is a classification model loosely based on biological neural networks such as those in the brain [112]. They generally consist of an input layer, one or more hidden computational layers and an output layer as shown in Figure 3.11. Each layer can have multiple "neurons" and each layer has connections between the neurons. These connections each have a weight which means that the value applied to the neuron is multiplied by the weight and then added to all the other inputs on the next neuron to give that neuron its input value. Not every neuron in one layer is connected to every neuron in the next layer, the network tries different configurations to find the optimal link network and weight configuration.

The network is trained by applying a series of inputs to the input layer, randomising the network connections and weights and calculating the outputs at the output layer. Either supervised or unsupervised learning can then be utilised. Supervised learning compares the outputs from the output layer with the known results for that set of inputs then feeds the error back to the hidden layers to change the weights and improve the output. Unsupervised learning allows the network to simply classify the inputs into a sensible series of categories.

3.3.6 Multi-Layer Perceptron ANNs

A Multi-Layer Perceptron (MLP) is a specific type of artificial neural network which uses at least 3 layers, an input layer, at least one hidden layer and an output layer as shown in Figure 3.11. The hidden and output layers use activation functions to determine the input of the one layer from the outputs of the previous layer.

The training of an MLP is done in two phases. Firstly known inputs are entered at the input layer and their outputs compared with known outputs. The weights of the network are then adjusted based on the error between these two values and the error is fed back to adjust the weights. This is known as back-propagation.

The second step is to take new data and pass it through the network using the final weight configuration and determine how well it is classified.

3.3.7 MLP ANNs Used in this Work

In this work two separate supervised MLP ANNs were trained and tested for each participant based on the features that had been calculated from the signals. The first ANN classified the movement state of the participant, ie standing still, walking or running. The second determined the movement speed of the participant. It was important that these tasks were done separately to allow fast walking to be distinguished from slow running at the same speed. This distinction needs to be made because although the volunteer might be moving at the same speed, different settings are needed for the leg for the two types of activity.

The supervised MLP ANNs used for this work were trained and tested using the following settings.

- Feed forward
- One input node for each feature
- One output node
- Tansig transfer functions for all nodes
- Two hidden layers containing 5 and 2 nodes
- Maximum number of epochs of 1000
- Maximum fail epochs of 10
- Learning rate of 0.01

- Gradient descent momentum and adaptive learning rate based backpropagation training function
- Performance function of MSE

These are the basic settings of the ANN within Matlab and had previously been found to be more than adequate for the classification task required.

The number of layers and hidden units in each ANN is determined by the GA.

3.3.8 Randomising Inputs

Before the features calculated from the raw signals were passed to the ANN their order was randomised as shown in Figure 3.12. The top row shows the original order the features are calculated in and this is based on the time of arrival of the signal used to calculate the feature. The bottom row shows how the order was randomised.

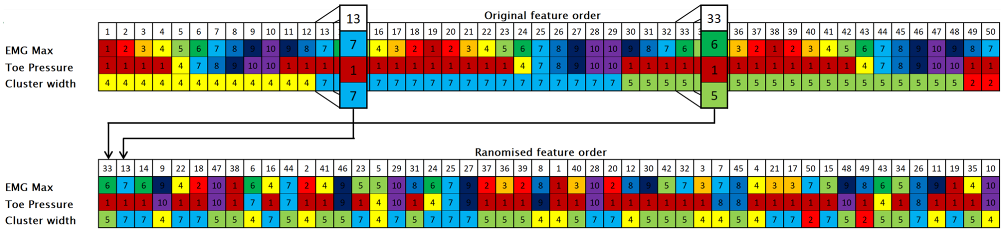


FIGURE 3.12: Randomising the input features from their original, sequential order

The reason for doing this was that in previous work it was found that the estimation by the ANN failed to reach certain values such as high, short bursts of speed and this was because the sequential nature of the data allowed the ANN to base its next prediction on the previous one. By randomising the data and removing the sequential nature of the features, each prediction had to be calculated on the values of the features in that time slot alone.

3.3.9 Ten Times Cross Validation

A proportion of each set of data was used to train and then test the ANN. This was done by taking the randomised set and splitting it into ten equal parts. 10 separate ANNs were then trained using this data with a sliding window used to select the proportion to use for training and for testing. Figure 3.13 shows how this window slides if 1/10 of the data is used and Figure 3.14 shows how this window slides if 4/10 of the data is used.

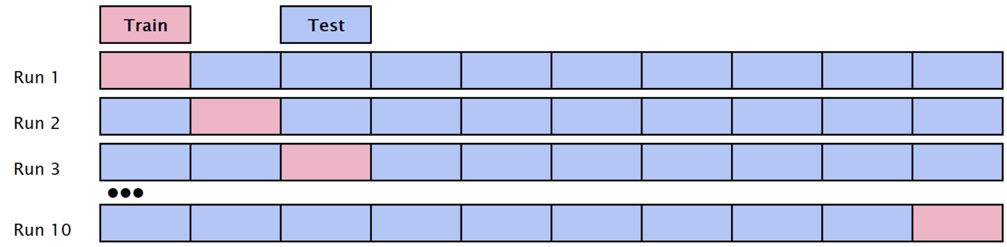


FIGURE 3.13: Cross validation showing how a 1 in 10 crossover might be carried out

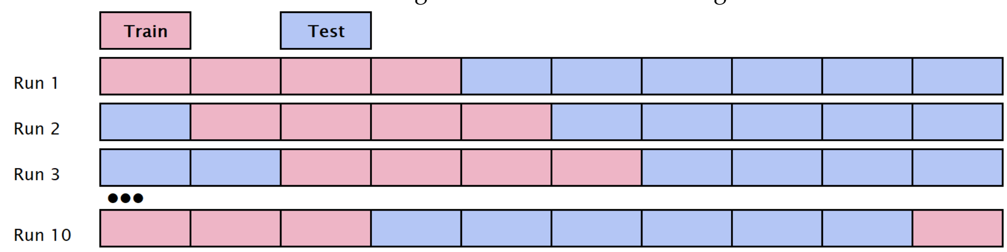


FIGURE 3.14: Cross validation showing how a 4 in 10 crossover might be carried out

3.4 Classification and Approximation

In order to determine the success of each ANN the original movement mode or speed were used as the supervised learning output.

3.4.1 Movement Mode

For the movement mode it was necessary to determine walking speed for each subject. From observation it was found that walking speed in all cases was between 5 and 7 Kph and as the treadmill allowed an exact speed to be set it was very simple to determine when the subject was walking or running.

However, it was found that there was noise and inaccuracy around the acceleration and deceleration phases of all movement and in particular during the changeover from running to walking. A gene was included to estimate walking speed for each individual and this was used as the crossover point in each case.

Even though this gene was successful it is still doubtful that this change from walking to running and vice versa can be considered accurate as the treadmill causes the subject to carry out unnatural movements during this changeover.

3.4.2 Movement Speed

The movement speed of the user was calculated by averaging the speed determined by the rotary encoder over a window of n samples, determined by the GA. This window size was not considered an issue for accuracy because the averaging simply overcame the problem of unequal numbers of ticks and would not exist in the real world.

3.4.3 MSE Performance Function

To determine the success of each ANN the MSE was calculated and stored along with that iteration's gene settings.

The ten times cross validation procedure previously described was used on each iteration of genes and the iterations showing the best average MSE were determined to be the most successful and put to the top of the list on the next sort of features for the GA.

3.5 Using a Genetic Algorithm

Initial work with the extracted features showed that there were a very large number of combinations for the feature extraction and artificial neural network settings. Clearly, this number of combinations would be impossible to process in a reasonable time. A genetic algorithm was utilised to optimise these settings and this section describes how this was done.

3.5.1 Gene Types

Three types of genes were used in the GA:

1 - System parameter genes

The values set by these genes were used to pre-process the input signals and create the settings for the building of the GA and neural network.

1. An Estimation of user's walking speed used to determine whether the user was walking or running
2. The number of speed readings to average over to smooth out the speed per user
3. The threshold signal value below which any EMG signal is removed to remove the background signal not related to the movement

4. The number of epochs the ANN is to be run for
5. The number of nodes in the hidden Layer (5, 7 or 9) of the ANN which had previously been proved to give the most accurate results
6. The number of hidden layers for the ANN

2 - Feature parameters

The values set by these genes were used while processing the input signals to extract the features from them.

1. Window size for average feature
2. Window size for maximum feature
3. Min for Spike Gap feature
4. Max for Spike Gap feature
5. Trigger size for Cluster Gap feature
6. Max for Cluster Gap feature
7. Min for Spike Width feature
8. Max for Spike Width feature
9. Trigger size for Cluster Width feature
10. Max for Cluster Width feature
11. Min for Pressure 1 feature
12. Max for Pressure 1 feature
13. Min Pressure 2 feature
14. Max for Pressure 2 feature
15. Window size for Accelerometer features

3 - Feature activators

These genes determined whether or not a feature was used in the ANN on this iteration. The list below is therefore a full list of all the features that could possibly be used for each iteration. The GA gave each of these genes a simple value of 1 or 0 and if the gene was 1 then the respective gene was used in the ANN in that iteration.

This is a novel technique whereby the chromosome chooses its own contents rather than varying in size which has not been found anywhere else in the literature.

1. Use raw EMG signal
2. Use average feature
3. Use maximum feature
4. Use Spike Gap feature
5. Use Cluster Gap feature
6. Use Cluster Width feature
7. Use Pressure 1 feature
8. Use Pressure 2 feature
9. Use Accelerometer 1 feature
10. Use Accelerometer 2 feature

3.5.2 Gene Structure

For all but the feature activator genes a minimum, maximum and resolution value was determined. The Feature activator genes simply indicate whether a feature should be used or not so could only have a value of 1 or 2. The genes used and their min, max and resolution values are shown in Figure 3.15.

Gene Name	WALK_SPD	SS_SPD	SZ_spike	SS_AVG	SS_MAX	MN_SpikG	MX_SpikG	BF_ClusG	MX_ClusG	BF_ClusW	MX_ClusW	PR1_max	PR1_min	PR2_max	PR2_min	SS_Acc	NT_Opt	MLP_typ	HID_Lay	Cycles	NET_Lay	USE_EMG	USE_SPG	USE_CLG	USE_CLW	USE_AVG	USE_MAX	USE_PR1	USE_PR2	USE_AC1	USE_AC2
Min	5	20	1.5	5	5	1	2	5	30	10	20	50	50	50	50	5	0	0	5	2K	0	1	1	1	1	1	1	1	1	1	1
Max	7	50	3.5	50	50	6	7	60	60	40	40	500	500	500	500	100	4	3	20	10K	3	2	2	2	2	2	2	2	2	2	2
Step	0.1	1	0.01	1	1	1	1	5	5	5	5	5	5	5	5	1	1	1	1	100	1	1	1	1	1	1	1	1	1	1	1

Index	
This symbol will be used in diagrams to represent this set of genes.	
Min: The maximum value for the gene	
Max: The minimum value for the gene	
Step: The step by which the gene can be adjusted.	

FIGURE 3.15: 31 genes were created each with a minimum and maximum value and the step by which they can be increased or decreased

An initial population of 50 individuals was created with random values for all genes calculated by generating a random number between the max and min value as shown by Equation 3.3.

$$startingvalue = Randomvalue(\frac{max - min}{resolution}) + min \tag{3.3}$$

Two checks needed to be made on the initial population before it could be used. These were:

1. Check that at least two genes had been selected as active from the ”Use feature” list.

2. Ensure that all max values were greater than their respective min values

The populations were then passed through 200 generations of evolution.

50 individuals and 200 generations were chosen because these values had been found to be the best balance between the stability of the MSE result and the length of time it took to process the experiment during previous experimentation. Appendix E gives as series of graphs for the MSE results showing how they stabilised within 200 generations.

3.5.3 Genetic Operators

After each iteration of the code the resulting chromosomes were ordered according to the best MSE and then several genetic operators were applied to them.

1 - Elitism

The best individual of each population was retained as an elite individual.

2 - Mutation

Each generation, n genes were chosen to be mutated. A gene was chosen at random to be mutated. If the gene was a binary flag it was switched, otherwise a new random value was generated for that gene using Equation 3.3.

3 - Crossover

A certain percentage of the chromosomes were crossed over on each iteration using the following procedure:

- Sort the chromosomes in ascending order of MSE size
- Process the required percentage of chromosomes in pairs and do crossover
- Generate a random number corresponding to a value between the current location and the end of the chromosome
- Swap the two chromosomes over at this point as shown in Figure 3.16
- Repeat until the end of the chromosome is reached

Figure 3.16 shows how two chromosomes would look throughout this process.

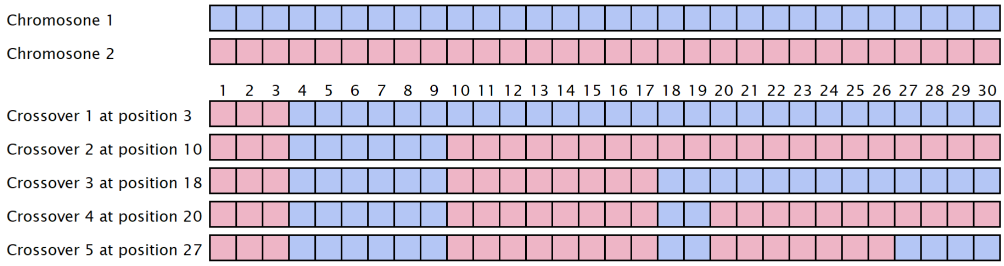


FIGURE 3.16: The crossover of two chromosomes showing how multiple crossover points can be used.

For each of the 30 runs the following procedure was carried out as shown in Figure 3.17.

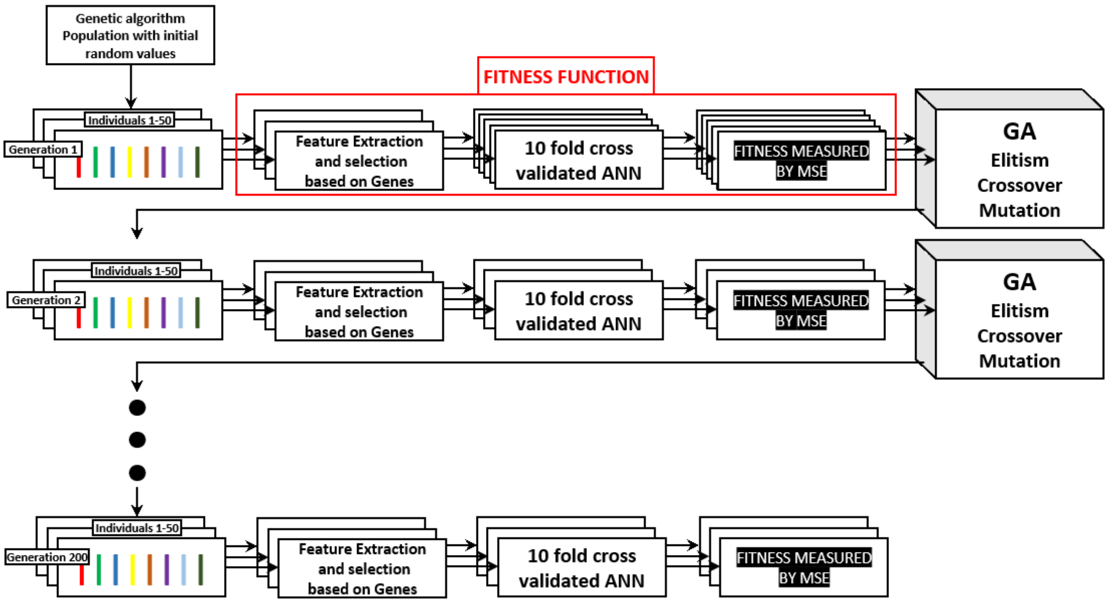


FIGURE 3.17: An initial population of 50 individuals is created by generating random numbers between the min and max for each gene. The genes are used to create 50 sets of features which are passed through 500 ANNs using 10 x cross validation to produce 500 MSE values. These values represent the fitness value of each individual and are then used to sort the individuals which are then passed through a GA where elitism, crossover and mutation are used to create the next population of 50 individuals with new values for their genes. This is repeated 200 times.

The 200 generations were then run as outlined in the list below:

1. For each of the 50 individuals, calculate the features from the raw signals using the feature parameters determined by the GA as shown in Figure 3.15 and Equation 3.3.
2. Randomise the order of the calculated features to avoid knowledge from the previous signal as described in Section 3.3.8.
3. Select 1/10 of the calculated features for training based on the 10 x cross validation as described in Section 3.3.9.

4. Train an ANN using only those features that have been chosen by their feature activator and the values chosen by the GA for the system parameters
5. Use the remaining 9/10 of the calculated features to test the ANN using cross validation (so 10 times per run)
6. Capture the MSE for this individual with this ANN
7. When all 50 individuals have been passed through their ANN order them according to their lowest MSE
8. carry out the elitism, mutation and crossover to create the next generation of the GA as described in Section 3.5.3.
9. Return to step 1 until all 200 generations have been completed.
10. At the end of this process there will be 1000 sets of genes each with 10 MSE (one per cross validation set) as shown in Figure 3.18

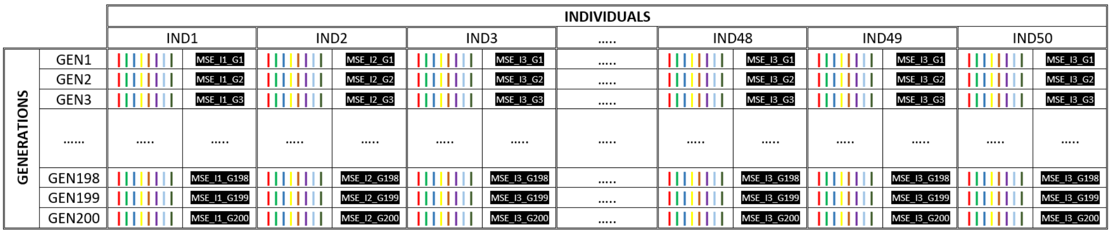


FIGURE 3.18: At the end of this process there are 1,000 sets of genes each with 10 MSE values

Chapter 4

Experimental Setup

This chapter describes how the sensors were attached to the wearable gait lab, how the wearable gait lab was tested and how the data was then gathered.

4.1 Introduction

Experiments consisted of asking volunteers to wear the wearable gait lab which consisted of pressure sensors, accelerometers, goniometers and EMG sensors.

To determine the movement mode and speed of the volunteer they were asked to walk and run on a treadmill which had a wheel sensor with a rotary encoder attached to it.

A safe method had to be found to mount these sensors on the subject without impeding their ability to move on the treadmill. As the goniometers were mounted on hinged struts these were used to help mount the other sensors.

4.2 The Wearable Gait Lab

In order to record the movements of a subject, a number of different sensors were used on different parts of the legs as listed below.

- EMG Sensor
- Six pressure sensors, one under the heel, toe and ball of each foot
- Four accelerometers, one on the thigh and calf of each leg
- A Wheel Sensor was attached to the treadmill

The sensors were mounted on a harness and worn as shown in Figure 4.1.

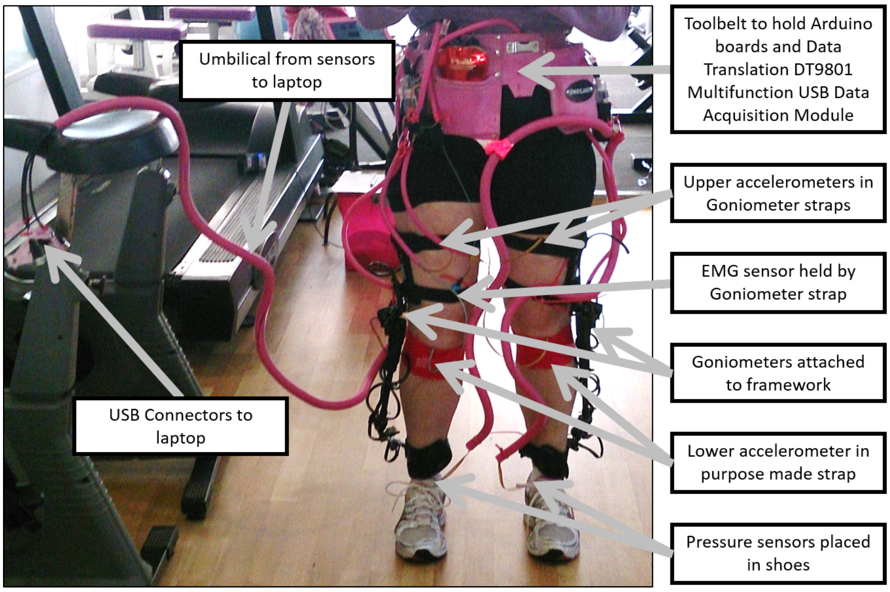


FIGURE 4.1: The layout of the sensors on a volunteer

Each sensor is discussed in the following sections.

4.2.1 Wheel Sensor

To determine at what speed the participant was walking or running at, a small wheel sensor was attached to the treadmill through an Arduino hobby board. Code within the Arduino counted each revolution of the wheel. An interrupt was then triggered at a frequency of 50Hz to read the wheel counter and then zero it ready for the next reading. From this reading the speed of the volunteer could be calculated in Km/h.

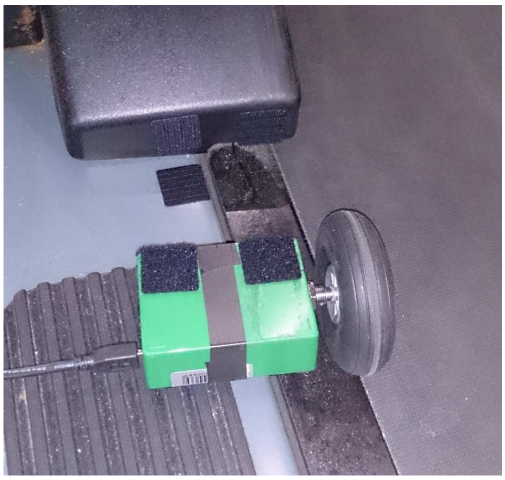


FIGURE 4.2: The speed sensor attached to the treadmill

The mounting of the wheel sensor on the treadmill was a simple touch fit as shown in 4.2. The number of revolutions counted in any given sample typically varied by one or two revolutions with neighbouring samples when travelling at a steady speed and so this produced a noisy signal. To overcome this, the value achieved was averaged over the last n readings. N was determined by the genetic algorithm.

4.2.2 EMG Sensor

An EMG sensor picks up the signals sent by the nerves through the body to control the muscles [79, 113]. The EMG sensor used for this research consists of:

- A Motion Lab Systems MA 317 A300 A3 Preamplifier
- An amplifier circuit to further increase signal levels
- A Data Translation DT9801 Multifunction USB Data Acquisition Module
- Data Translation DT Chartrecorder software

The positioning of the EMG sensor was initially considered to be quite significant, requiring a large amount of experimentation. However, after several tests with different people it proved to be considerably easier than expected. Indeed, when positioning the EMG sensor on the amputee it was simply a case of putting the sensor securely inside the socket. Then, with a small amount of adjustment, an excellent signal was achieved.

Once secured to the subject, the EMG was connected to the Data Acquisition Module which was in turn connected to a laptop as shown in Figure 4.1.

4.2.3 Pressure Sensors

The walking and running gait has been extensively researched for many centuries [108].

Although the walking and running gait may look and feel very straightforward there are many small movements which make up the gait that indicate what is happening or what is about to happen. This means that while it may appear that everyone walks in a similar way each person's gait is very individual to them.

FIGURE 4.3: The pressure sensors used

Gait analysis has become an advanced science in its own right [114]. In fact an individual's gait has proved effective in determining their gender and identity [115–117].

The pressure sensors shown in Figure 4.3 were used in this work to identify the pressure in 3 parts of the foot at different events during the walking gait. The pressure sensors used were:

- Round Interlink FSR400 7.62 mm x 0.3 mm

- Active area (diameter) 5.08 mm
- Pressure reading range 0.2 N - 20 N
- Arduino hobby board

The sensors were connected to an Arduino board which was then attached to a laptop as shown in Figure 4.1.

For the purposes of this work there were only two important landmarks within the walking gait that needed to be examined. These are "Heel Strike" and "Toe Off" as shown in Figure 3.1. These two events mark the start and end of the stance and swing phases, the two points in the movement of the leg when it goes from loading to unloading.

To record information about the participant's gait three pressure sensors were used. These were placed on the three parts of the foot shown in Figure 3.7.

1. Pressure sensor 1 was placed directly under the big toe as this is typically the last part of the foot to leave the ground at the "toe off" event
2. Pressure sensor 2 was placed as close as possible to the main pad of the ball of the foot
3. Pressure sensor 3 was placed under the heel of the foot, as far back as possible to capture the "heel down" event

4.2.4 Accelerometers

The accelerometers used are shown in Figure 4.4. Accelerometers were placed on the front of both calves and both thighs as shown in Figure 4.1.

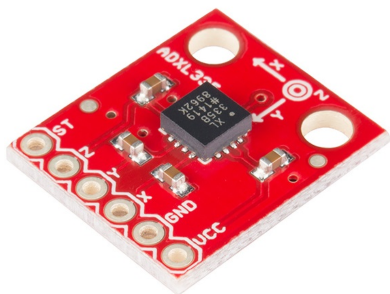


FIGURE 4.4: The accelerometers used

The specifications of the accelerometers were:

- ADXL335 low power, complete 3-axis accelerometer with signal conditioned voltage outputs
- 4 mm x 4 mm x 1.45 mm LFCSP
- Single-supply operation: 1.8 V to 3.6 V
- 10,000 g shock survival

- Measurement Range ±3 ±3.6 g
- Arduino hobby board

The sensors were connected to an Arduino board which was then attached to a laptop as shown in Figure 4.1.

4.3 Signal Capture

Each sensor was attached to a laptop. The EMG sensor was attached through the DAQ unit which allowed the signal to be captured. The signal capture rate for the EMG was set to 50Hz.

The pressure sensors, accelerometers, goniometers and wheel sensor were attached to the laptop through one of three Arduino. In each case, code was written to capture the signal at along with its time stamp.

4.3.1 Pre-Processing the EMG Signal

Before features were extracted from the signals basic pre-processing was carried out. This consisted of:

- Synchronising the gathered signals using their associated timestamps
- Normalise all signal values to be between 0 and 1

4.4 Data Capture

Once the sensors were prepared they were mounted on a harness which could be worn by the subjects as shown in Figure 4.1.

A total of eight subjects were tested as outlined in Table 4.1.

Before beginning the tests it was imperative that a test walk/run was made to ensure the safety of the subject. Once the equipment was safely attached the subject was asked to start the treadmill and then walk at a comfortable pace. Once the subject was comfortable walking they were asked to increase the treadmill to a comfortable running pace. Subjects 2, 3 and 4 were able to run at a high pace and were asked to do this

	Gender	Age	Top Running Speed [Km/h]
Subject 1	Female	32	7.0
Subject 2	Male	27	12.0
Subject 3	Male	28	14.0
Subject 4	Male	36	12.0
Subject 5	Female	50	10.0
Subject 6	Male	35	-
Subject 7	Male	26	12.0
Subject 8	Male	22	11.0

TABLE 4.1: This table shows the gender, age and running speed for each subject

when possible. Subject 6 is an above knee amputee and was unable to run on a treadmill.

After running for as long as they felt comfortable they were asked to return to a walking pace and then stop the treadmill.

Chapter 5

Results

Eight volunteers walked/ran on the treadmill between one and four times giving a total of 17 sets of data as shown in Table 5.1. Only one of the eight volunteers was an amputee because it was very difficult to recruit more than one. However, this volunteer was unable to run on a treadmill as this is very difficult for a prosthesis wearer.

	Gender	Runs
Subject 1	Female	2
Subject 2	Male	2
Subject 3	Male	2
Subject 4	Male	4
Subject 5	Female	4
Subject 6	Male	1
Subject 7	Male	1
Subject 8	Male	1

TABLE 5.1: This table shows the gender and number of runs for each subject

Each of these 17 sets of data was passed through the full GA/ANN system twice, once to generate an optimal ANN to determine the movement state of the volunteer (stand/walk/run) and once to generate an optimal ANN to determine their speed of movement giving 30 sets of results.

Each GA had a population of 50 individuals and 200 generations and each ANN was run 10 times with cross validation giving a total of more than 3 million results.

This chapter presents these results along with discussion.

5.1 Calculation of Results

The success or failure of an individual within a population was measured by the resulting MSE from the artificial neural network when comparing the expected result with the predicted result. The MSE was chosen, rather than the RMSE, as it was found to have larger variations which helped to prevent the GA finding local minima.

5.1.1 Speed Estimation

For speed estimation the speed the treadmill was actually travelling at was compared with the speed estimated by the artificial neural network to create the relevant MSE. In the previous work, where the parameters were chosen manually, rather than with the GA, a generally good estimation of the speed was achieved, however, there was a tendency for the output to fail to predict higher speeds and be less accurate during the increase and decrease of speeds.

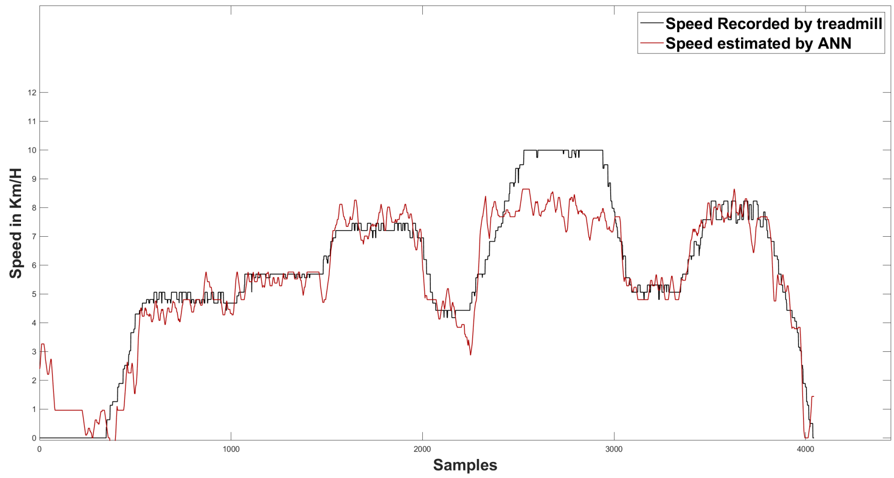


FIGURE 5.1: Estimation of speed for one run as calculated by previous work. Note that highest speeds are not accurately predicted.

Figure 5.1 shows the output from the best ANN created in the previous work using the standard settings determined by trial and error for one dataset.

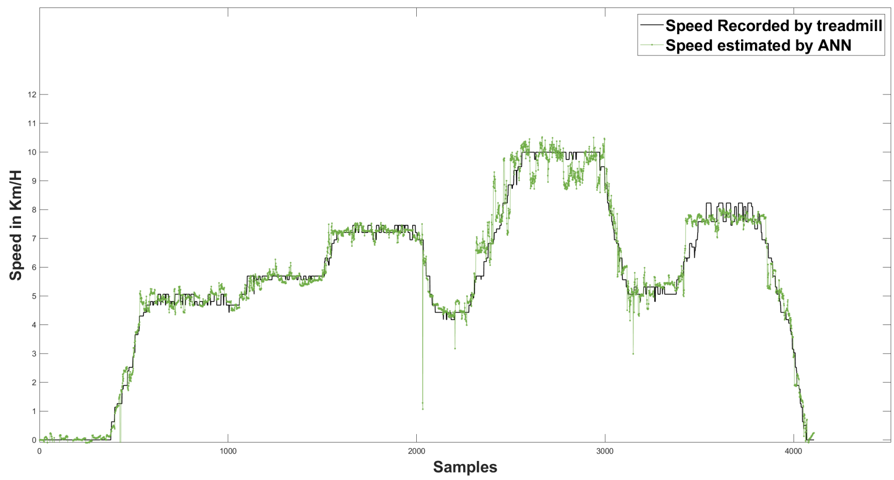


FIGURE 5.2: Estimation of speed for the same run as Figure 5.1 calculated by the new work. Note that highest speeds are now accurately predicted. A full list of all these graphs is shown in Appendix C

Figure 5.2, in contrast, shows the same output from the best ANN created in this work with the settings determined by the GA for the same dataset. As can be seen, the generalisation in Figure 5.2 is closer to the original speed than in Figure 5.1. In particular, it can be seen that the prediction at the highest speed and at the acceleration and deceleration points, more closely matches the correct value.

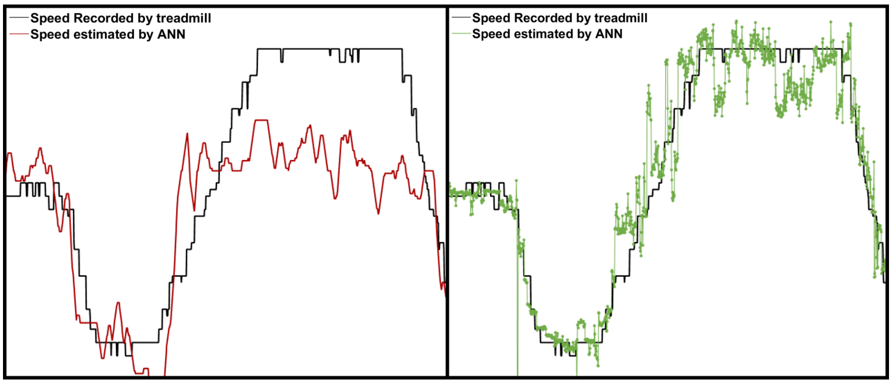


FIGURE 5.3: A comparison of the previous work, in red, and the current work, in green over the highest part of the subjects running.

This result is confirmed by the difference in the MSE values for the previous and current work. As can be seen in Table 5.2, the MSE has dramatically improved from 1.13^0 obtained in the original work to 8.51^{-4}. Also, the RMSE has improved from 1.06^0 to 2.91^{-2} respectively. Figure 5.3 shows the detail of the fastest speed from the previous and current work.

Work	MSE	RMSE
Original MSC Work	1.13^0	1.06^0
This Work	8.51^{-4}	2.91^{-2}

TABLE 5.2: A comparison of the MSE and RMSE of the previous work and current work on the same data set.

5.1.2 Movement State Approximation

Movement state approximation showed little improvement on the previous work with the movement state being approximated to a similar level of accuracy as before as shown in Table 5.3. An example of the outcome is shown in Figure 5.4.

The lack of change is not surprising as this is a much simpler task for the ANN to achieve. Movement state approximation requires the ANN to choose from three discrete categories whereas Speed estimation requires it to choose on a varying scale.

Work	**MSE**	**RMSE**
Original MSC Work	5.70^{-2}	2.39^{-1}
This Work	3.72^{-4}	1.93^{-2}

TABLE 5.3: A comparison of the MSE and RMSE of the previous work and current work on the same data set.

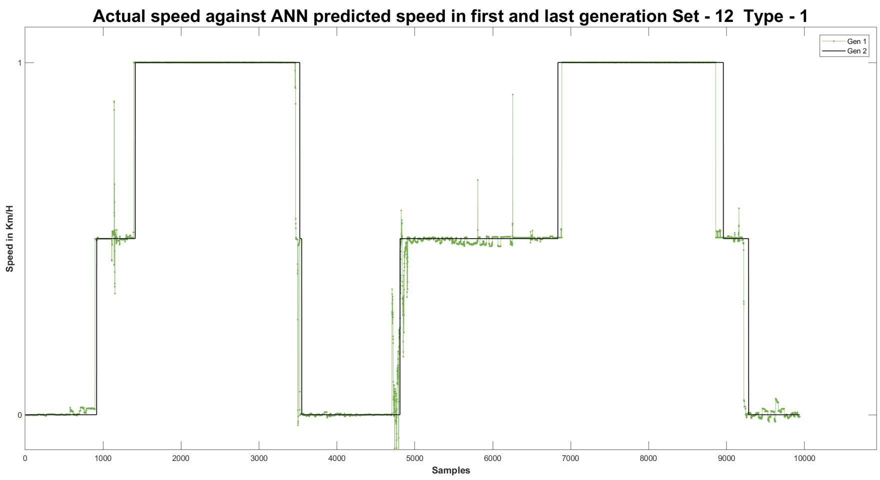


FIGURE 5.4: A typical Example of the Movement State Approximation results. A full list of all these graphs is shown in Appendix D

5.2 Evolution of Genetic Algorithm

To determine the progress and effectiveness of the evolution of the GA, the lowest MSE of each generation was captured and plotted over the generations, as shown on the red line in Figure 5.5. The progression of the mean of the MSE in each generation is plotted in blue

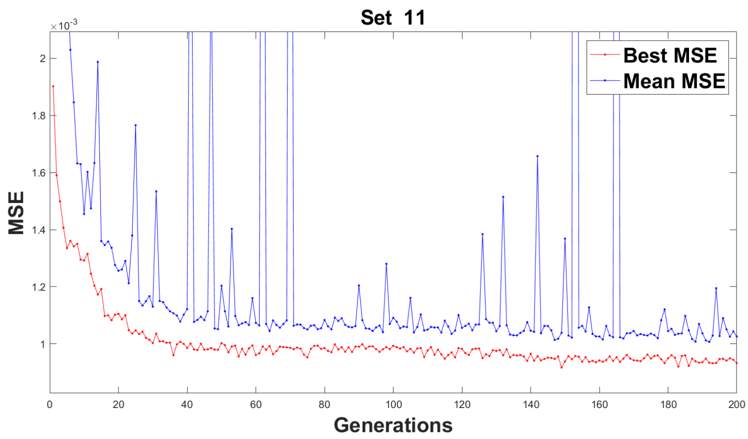


FIGURE 5.5: This graph shows the decrease in the best MSE in each generation over 200 generations for speed estimation in red and the decrease in the average of the MSE's of all 50 individuals in each generation over 200 generations for speed estimation in blue.

In Figure 5.6 it can be seen that the GA created noise to produce much higher MSE's on some generations and this was found to help avoid local minima by creating significant variations.

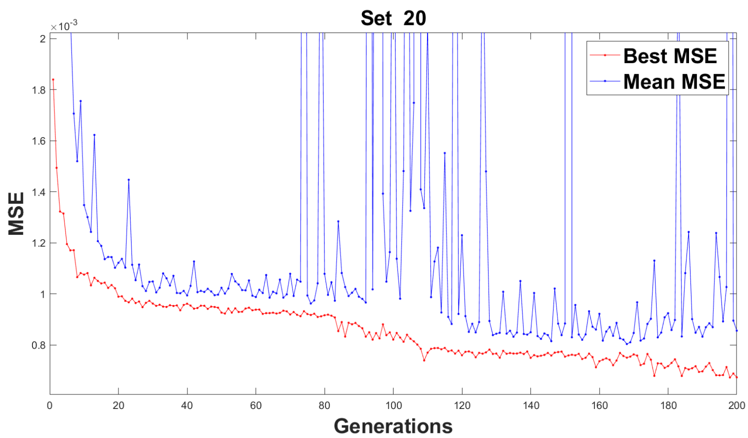


FIGURE 5.6: This graph shows the decrease in the best MSE over 200 generations for a different dataset showing how a change around the 100 generation mark has caused the MSE's for all individuals to drastically increase but subsequently leading to a marked decrease in thus avoiding a local minima.

A full list of all these graphs is shown in Appendix E showing the results for every dataset being passed through the best network found for each dataset.

5.3 Choice of Gene Settings for Individuals

GENERATIONS	VALUE FOR GENE | FOR EACH INDIVIDUAL						
	IND1	IND2	IND3	.....	IND48	IND49	IND50
GEN1	8	6	20	.....	9	19	14
GEN2	1	17	13	.....	10	14	8
GEN3	14	14	10	.....	19	7	18
......	.....	.....	.....	.....	.....	.....	.....
GEN198	17	17	17	.....	17	17	17
GEN199	17	17	17	.....	17	17	17
GEN200	17	17	17	.....	6	17	17

GENERATIONS	HOW MANY INDIVIDUALS HAVE EACH VALUE														
	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
GEN1	4	3	6	2	6	2	2	2	4	2	1	3	5	4	4
GEN2	2	5	9	1	4	1	1	4	5	1	1	4	4	3	5
GEN3	3	6	7	0	4	0	2	4	7	1	0	4	4	3	5
......															
GEN198	3	0	0	0	0	4	0	0	0	1	0	42	0	0	0
GEN199	2	0	0	0	0	1	0	0	0	0	0	47	0	0	0
GEN200	2	0	0	0	0	2	0	0	0	0	0	46	0	0	0

FIGURE 5.7: The first table shows the value of one gene for each of the 50 individuals over 200 generations. The second table shows every possible value for this gene across the top and then shows how many individuals had this value in each generation.

The GA was used to make a choice for the settings for each feature for each individual. Over the course of the 200 generations, the GA made clear choices on every occasion. Figure 5.7 shows how one gene developed over the 200 generations for all 50 individuals.

In the first table it can be seen that the 50 individuals were assigned random values for the gene in question in generation 1. However, by gene 200 all but one of the individuals has chosen the same value of 17 for this gene.

The second table shows all the possible values for this gene across the top (6 - 20) and then shows how many individuals had that value in each generation. As can be seen, in Generation 1 the number holding each possible value has a reasonably even distribution. However, by the final generation there are only 2 individuals each with a value of 6 and 11 and the other 46 all have a value of 17.

At the end of the 200 generations, the individual with the lowest MSE for each set was examined and the results of this are shown in Tables 5.8 and 5.9.

- The top box (lines 1-16) shows the values determined by the GA for the various features. Those values coloured green were the ones the GA decided to use as determined by the last box of values. Where two lines have been coloured using the same shade of green these are dependent on each other.
- The second box (lines 17-21) shows the settings determined by the GA for the ANN.
- The last box (lines 22-31) shows which features the GA decided to use.
- The numbers 11 to 27 indicate the individual runs carried out by each volunteer - the chosen range is historical

- Where several cells are enclosed in a thick border this indicates that these runs belong to the same volunteer eg 11,12,13 and 14
- The Gene number and name is listed down the side
- The pale yellow cells highlight features that the GA did not select to use
- The green cells highlight the values of the parameters for genes that have been selected for use
- Where two lines are highlighted together in the same shade of green they relate to each other eg a minimum and maximum value for the same feature

Of particular note from the results is the fact that for Movement State Approximation the new pressure features (lines 28 and 29) which approximated so well to the movement state has been chosen in virtually every case while the new accelerometer features (lines 30 and 31) which approximated so well to the movement speed are not used as would be expected.

However, for Speed Estimation the new accelerometer features (lines 30 and 31) are used in the majority of cases but so are the the new pressure features (28 and 29). This shows how the GA is able to find useful information in features that may not appear useful to a human observer.

Also of note are some of the parameter values for features that have not been chosen. eg in Table 5.8, Movement State Approximation, the value for Gene 28 for individual 25 has been set to 1 meaning that the Pressure 1 feature will not be used. When the values of the Pressure 1 feature parameters are investigated it is found that the minimum and maximum values (lines 12 and 13) have been set by the GA so that the maximum is less than the minimum ie minimum = 175 and maximum = 95. This would have made this feature unusable and so the GA has eliminated it thus showing that the GA is making sensible choices.

In order to illustrate this evolution, a scattergram plot was created for each gene, for each data set as shown in Figure 5.10. The red numbers indicate the following.

1. The x axis shows the generations.
2. The y axis shows all the possible values for this gene, in this case 6-20.
3. Each red dot shows that an individual had that value set for that gene in that generation.

MOVEMENT STATE APPROXIMATION																		
Gene No.	Gene \ Set No.	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	WALK_SPD	6	6.5	5.3	5.4	6.8	5.2	7	5.5	6	6	6.7	6.5	6.9	6.3	6.1	6.4	5.1
2	SS_SPD	47	32	40	50	21	22	48	28	48	50	42	29	40	34	22	50	50
3	SZ_spike	2.62	3.08	1.73	1.59	3.33	1.63	1.84	1.53	3.13	3.31	2.86	2.78	1.93	2.53	1.55	3.26	2.15
4	SS_AVG	46	45	49	49	50	43	46	31	50	43	22	13	36	48	23	41	50
5	SS_MAX	43	50	50	49	36	50	41	48	45	13	50	15	49	49	21	21	15
6	MN_SpikG	2	4	5	3	4	5	5	3	6	6	6	6	2	2	4	6	3
7	MX_SpikG	7	5	4	7	5	3	3	7	7	5	7	7	5	4	6	5	3
8	BF_ClusG	20	35	10	10	25	10	10	20	15	25	20	10	25	35	35	10	10
9	MX_ClusG	55	35	35	35	55	35	50	35	55	60	55	50	45	60	40	60	40
10	BF_ClusW	25	15	40	30	40	20	30	35	20	30	20	25	25	40	35	40	30
11	MX_ClusW	30	30	40	40	35	40	40	30	35	30	40	40	30	40	30	35	25
12	PR1_min	230	145	330	190	455	325	340	265	65	65	70	180	140	290	175	290	110
13	PR1_max	340	425	415	465	85	275	340	395	290	295	310	295	295	325	95	330	445
14	PR2_min	250	70	215	145	100	135	90	280	430	70	180	290	290	365	475	120	90
15	PR2_max	85	90	315	160	125	110	105	485	110	230	280	320	355	360	75	265	285
16	SS_Acc	28	64	15	63	82	49	99	64	83	32	68	57	33	22	11	78	65
17	NT_Opt	1	3	3	4	1	3	1	2	4	4	3	1	3	2	4	1	1
18	MLP_typ	2	3	1	2	2	3	2	3	1	3	3	2	3	2	3	1	3
19	HID_Lay	13	8	8	14	16	7	12	15	19	13	18	18	8	9	16	14	11
20	Cycles	5600	9400	3900	2600	8200	9500	9000	8500	6700	4100	7200	7200	8900	6400	4800	5600	5100
21	NET_Lay	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
22	USE_EMG	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	2	1
23	USE_SPG	2	2	1	1	2	2	1	2	2	2	1	2	1	2	2	2	2
24	USE_CLG	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
25	USE_CLW	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
26	USE_AVG	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2	2	2
27	USE_MAX	2	1	2	2	2	2	2	1	2	2	2	2	2	2	2	1	2
28	USE_PR1	2	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	2
29	USE_PR2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
30	USE_AC1	1	1	1	1	2	2	1	2	2	1	1	1	1	2	1	1	1
31	USE_AC2	1	1	2	1	1	2	1	1	1	1	1	1	1	1	1	1	1

FIGURE 5.8: This table shows the best individual for each data set after 200 generations for Movement State Approximation.

SPEED ESTIMATION																		
Gene No.	Gene \ Set No.	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	WALK_SPD	6.4	5.6	6.7	6.7	5.9	5.4	5.5	6.8	6.1	5.9	6.3	5.3	5.1	5.6	5.6	6.4	6.2
2	SS_SPD	50	50	48	48	25	32	49	50	21	50	21	33	21	24	38	50	50
3	SZ_spike	2.71	1.59	3.38	2.68	3.22	2.85	2.84	2.71	3.5	3.29	2.57	2.32	2	2.37	3.27	3.26	2.15
4	SS_AVG	49	50	48	48	49	49	49	50	50	50	48	50	50	50	45	50	50
5	SS_MAX	50	45	32	35	50	23	48	38	50	44	48	48	35	38	44	19	50
6	MN_SpikG	3	6	6	3	6	4	6	5	4	3	5	6	6	6	6	6	3
7	MX_SpikG	3	4	5	3	5	3	5	5	4	4	6	5	3	7	4	6	3
8	BF_ClusG	10	10	25	15	35	15	10	20	10	10	15	10	20	30	25	10	15
9	MX_ClusG	60	35	45	50	45	55	60	60	40	40	55	35	60	60	35	55	35
10	BF_ClusW	35	35	40	20	40	25	20	35	15	35	40	40	35	40	35	25	30
11	MX_ClusW	35	35	40	30	40	35	40	30	30	25	30	30	35	40	40	25	25
12	PR1_min	340	135	500	200	100	265	340	365	285	320	70	180	140	295	435	285	200
13	PR1_max	440	470	500	255	225	380	315	490	305	410	245	275	400	420	485	330	440
14	PR2_min	215	85	285	460	490	210	65	70	325	345	465	210	145	140	180	120	60
15	PR2_max	60	90	350	135	165	115	170	175	400	405	315	310	295	325	295	275	85
16	SS_Acc	99	99	98	99	100	70	61	100	36	20	76	65	17	65	14	18	34
17	NT_Opt	2	3	1	1	3	2	2	3	2	2	1	1	1	3	1	1	3
18	MLP_typ	3	3	2	1	1	3	1	1	3	2	1	2	1	2	3	1	2
19	HID_Lay	17	19	10	12	8	7	13	13	10	14	15	20	13	18	20	12	12
20	Cycles	7600	3600	2300	6500	6300	7500	9800	9100	5300	7400	6500	4400	3300	8600	8100	4200	2300
21	NET_Lay	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
22	USE_EMG	1	2	1	1	1	2	1	1	1	1	2	1	1	1	1	2	1
23	USE_SPG	2	2	2	2	2	2	2	1	1	2	1	2	1	1	2	2	2
24	USE_CLG	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
25	USE_CLW	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
26	USE_AVG	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
27	USE_MAX	2	2	2	1	2	2	2	1	2	2	2	2	2	2	2	2	2
28	USE_PR1	2	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	2
29	USE_PR2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
30	USE_AC1	2	2	2	2	2	2	1	2	2	2	2	2	2	1	1	1	2
31	USE_AC2	2	2	2	2	2	2	1	2	2	2	1	1	1	2	2	2	2

FIGURE 5.9: This table shows the best individual for each data set after 200 generations for Speed Estimation.

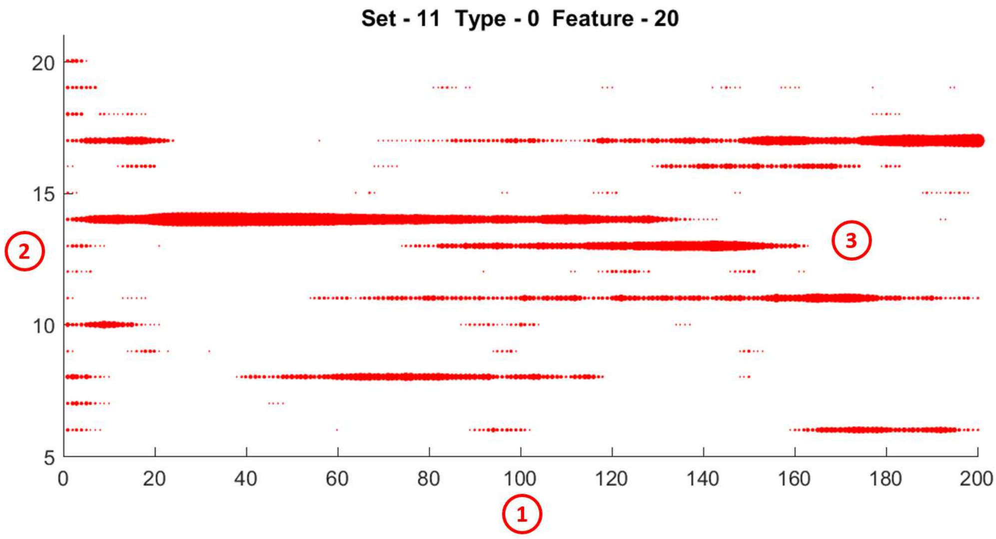


FIGURE 5.10: A visualisation of the evolution of one gene for every individual over 200 generations. Circle 1, the x axis, shows the number of generations. Circle 2, the y axis, shows every possible value the gene can hold. Circle 3 shows the dots which have been sized depending on how many individuals hold that value for that gene.

The size of the dot represents how many individuals held that value in that generation. As can be seen, there are roughly equal sized red dots for every y axis value in generation one, equating to the random distribution of values in line one of the second table in Figure 5.7. But, by generation 200 the red dot for value 17 is by far the largest, again equating to the second table in Figure 5.7. These evolution plots allowed the results of the evolution to be quickly evaluated.

Taking the Spike Gap Feature for Movement State Approximation as an example, line 3 of Figure 5.8 shows the values for the size of the spike as chosen by the GA. Looking at sets 21, 22, 23 and 24, which were all generated by the same participant, it can be seen that the values chosen by the GA were 2.86, 2.87. 1.93 and 2.53 respectively. It can also be seen from line 24 of Figure 5.8 that the gene used to determine if this feature would be used decided not to use the feature in the case of the highest and lowest spike size values. Figure 5.11 shows the evolution plots for feature 3 for sets 21, 22, 23 and 24.

It can be seen from Figure 5.11(C), the lowest spike value determined for this participant, that the GA started to shift position on its determination of this value towards the end of the generations, moving the value further up towards that determined for the other sets.

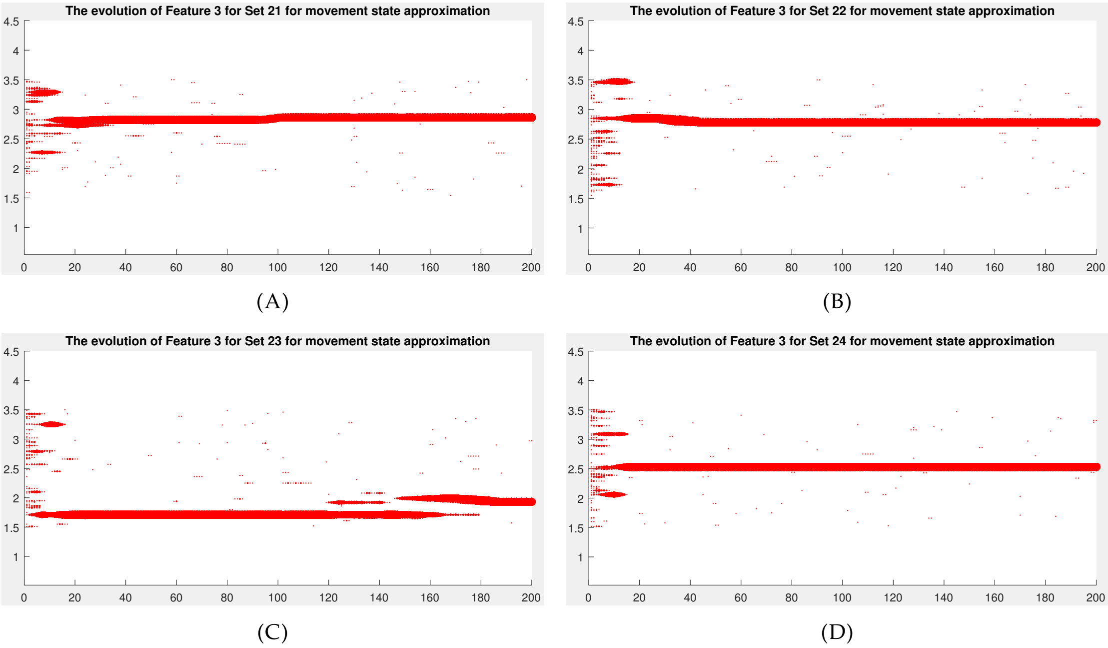


FIGURE 5.11: The evolution of Feature 3, the spike size, for sets 21, 22, 23 and 24, all of which were created by the same participant.

Figures 5.12 and 5.13 show the evolution plots for genes 6 and 7, the minimum and maximum values used in the determination of the spike gap feature. Again, it can be seen that for Set 23 there was uncertainty around the final best value for this gene.

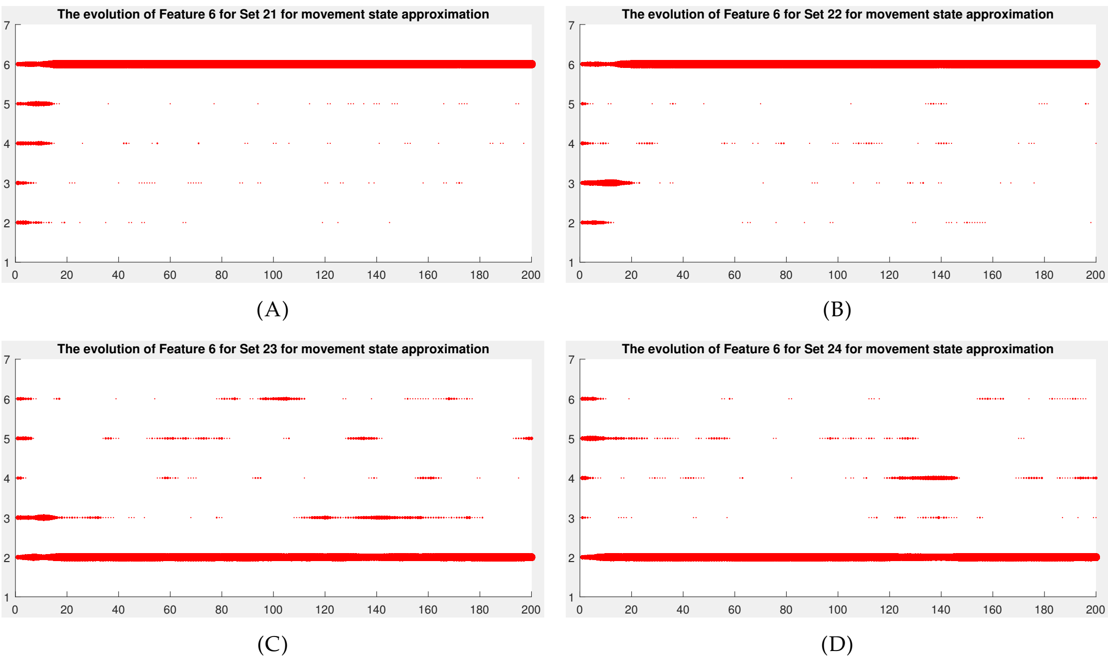


FIGURE 5.12: The evolution of Feature 6, the minimum spike gap, for sets 21, 22, 23 and 24, all of which were created by the same participant.

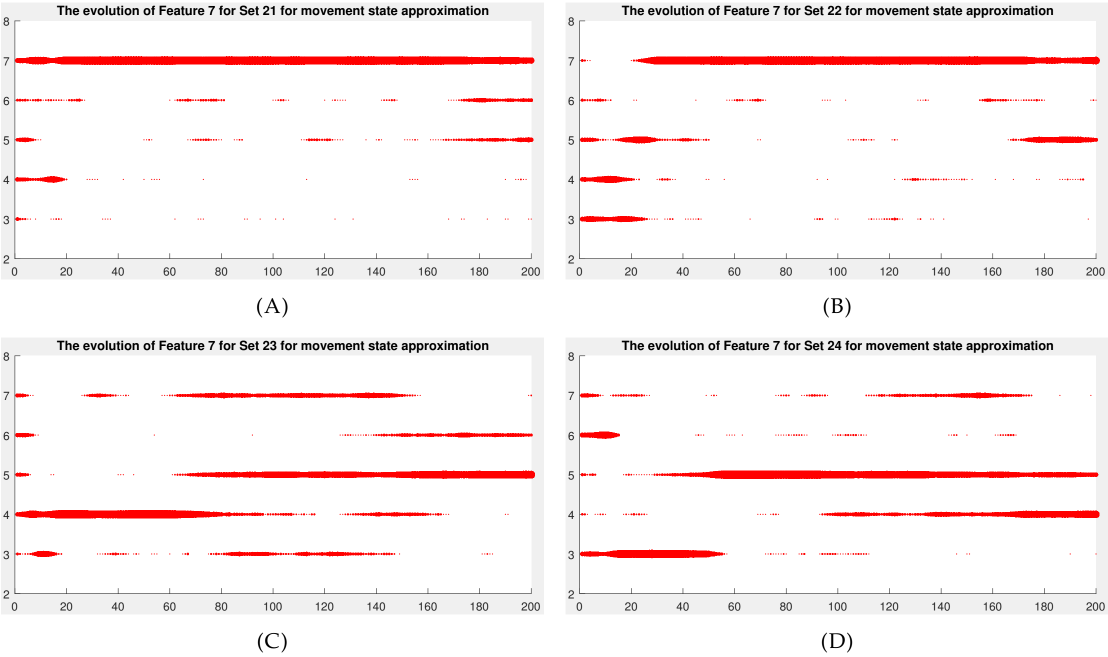


FIGURE 5.13: The evolution of Feature 7, the maximum spike gap, for sets 21, 22, 23 and 24, all of which were created by the same participant.

Figure 5.14 shows the gene that was used to determine if the Spike Gap feature would be used for sets 21, 22, 23 and 24. As can be seen, for set 23, where there was uncertainty about the value to choose, the GA has chosen not to use this feature for the most part.

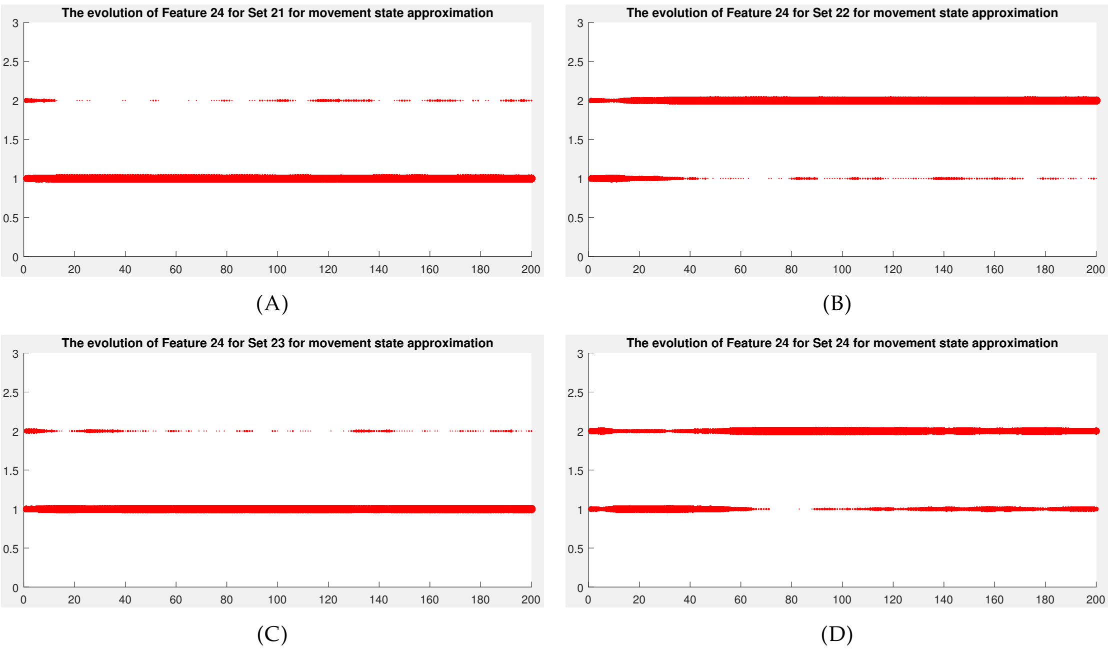
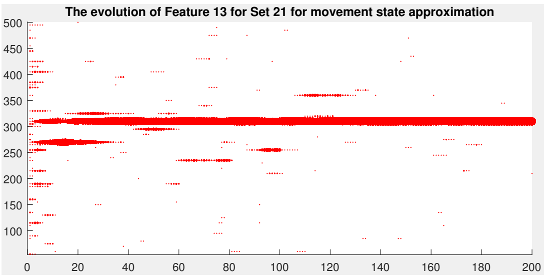
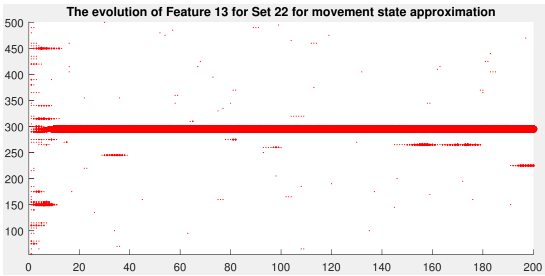


FIGURE 5.14: The evolution of Feature 24, the option to use the spike gap feature, for sets 21, 22, 23 and 24, all of which were created by the same participant.

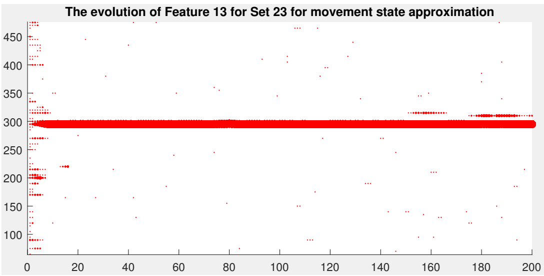
Figures 5.15 and 5.16 show the evolution of the maximum pressure setting for the pressure feature on the left leg for sets 21-24 (Figure 5.15) and sets 11-14 (Figure 5.16). The first four were created by one volunteer and the second four by a different volunteer.



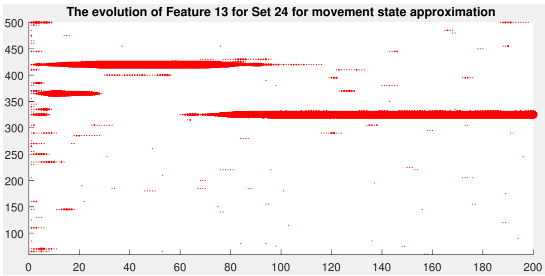
(A)



(B)



(C)



(D)

FIGURE 5.15: The evolution of Feature 13, the maximum pressure setting for pressure feature 1, for sets 21, 22, 23 and 24, all of which were created by the same participant.

While there are similarities between the plots created by the same person, there are marked differences between the plots for the two different people. For example, Figures 5.15A to 5.15D all show a final value of around 300 while Figures 5.16A to 5.16D show a final value between 350 and 450.

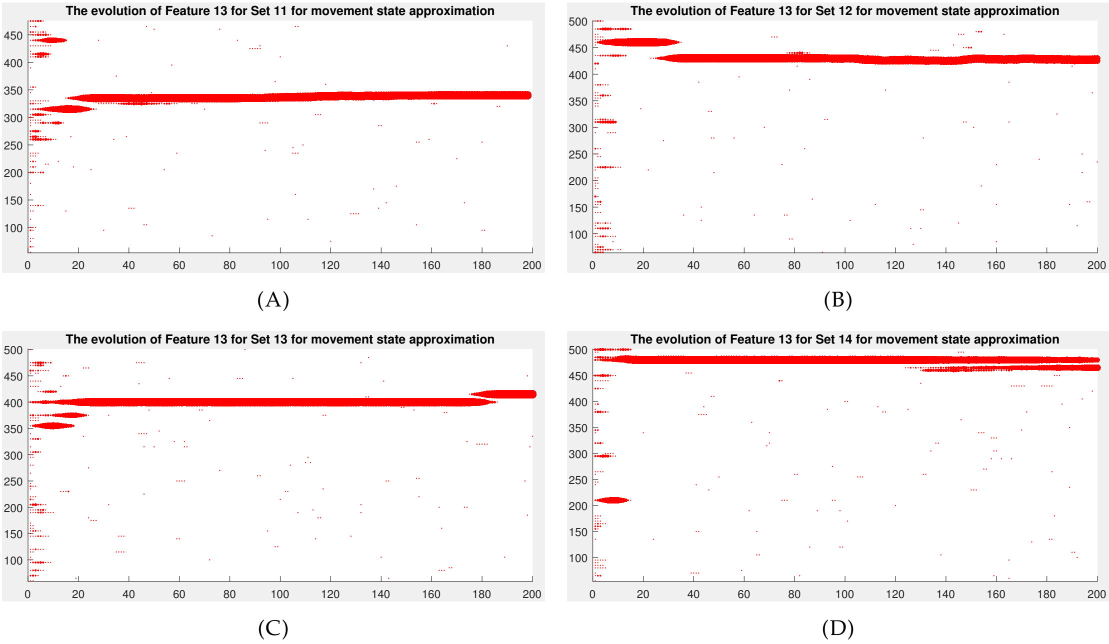


FIGURE 5.16: The evolution of Feature 13, the maximum pressure setting for pressure feature 1, for sets 11, 12, 13 and 14, all of which were created by the same participant.

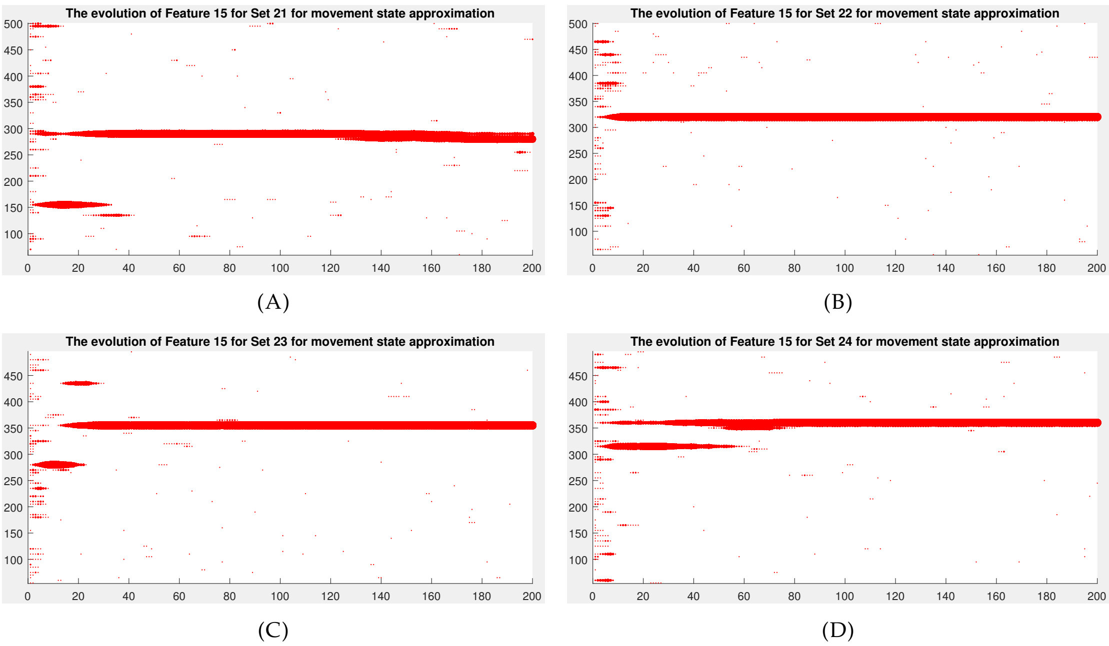
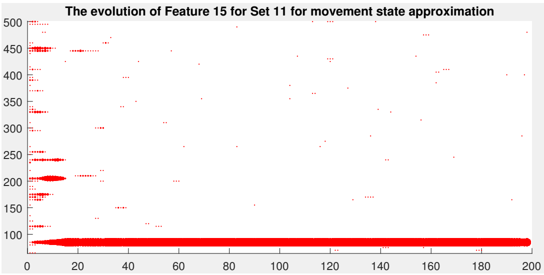
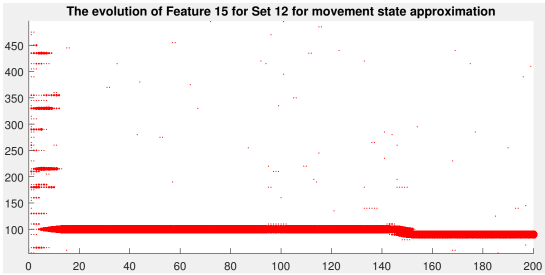


FIGURE 5.17: The evolution of Feature 15, the maximum pressure setting for pressure feature 2, for sets 21, 22, 23 and 24, all of which were created by the same participant.

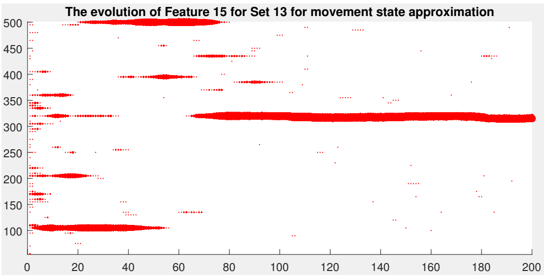
Figures 5.17 and 5.18 show the evolution of the maximum pressure setting for the pressure feature on the right leg for sets 21-24 (Figure 5.17) and sets 11-14 (Figure 5.18). The first four were created by one volunteer and the second four by a different volunteer. While there are similarities between the plots created by the same person, there are marked differences between the plots for the two different people. For example, Figures 5.17A to 5.17D all show a final value of around 300 while Figures 5.18A to 5.18D show a final value of below 100.



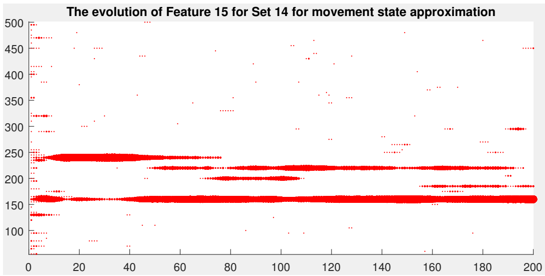
(A)



(B)

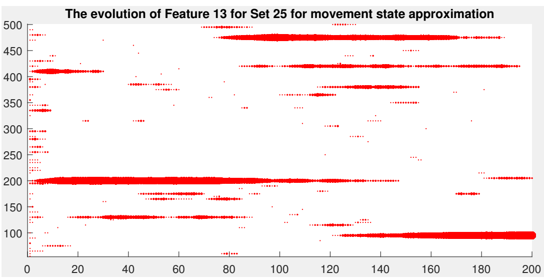


(C)

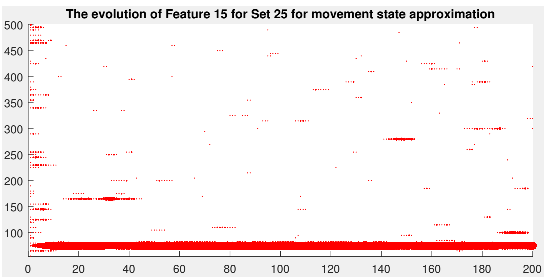


(D)

FIGURE 5.18: The evolution of Feature 15, the maximum pressure setting for pressure feature 2, for sets 11, 12, 13 and 14, all of which were created by the same participant.



(A)



(B)

FIGURE 5.19: The evolution of Features 13 and 15, the maximum pressure setting for pressure features 1 and 2, for set 25 who had an amputation.

Figure 5.19 shows the evolution of the 2 pressure feature maximums for the amputee where Figure 5.19A shows the results from the prosthetic limb. It is interesting to note that the GA struggled to get a clear result for this feature.

5.4 Evolution of Genes Across All Individuals

Once the plots of the evolution of all the genes were created it was interesting to examine them for each feature across all sets.

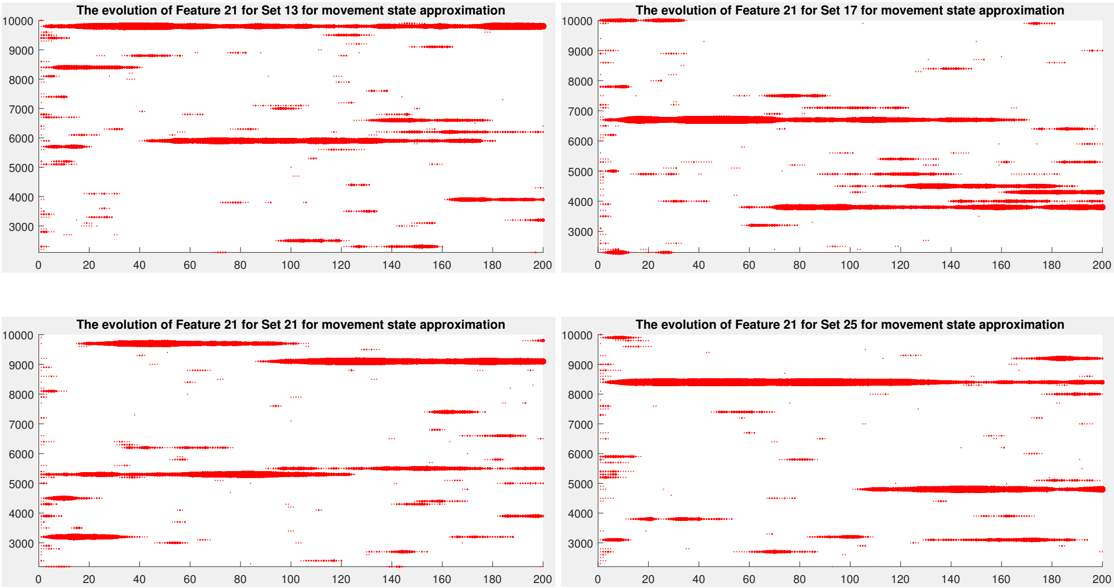


FIGURE 5.20: The evolution of feature 21 - Number of Epochs - for a sample of sets

For example, the evolution of the number of epochs for the ANN, shown in Figure 5.20, illustrates how this feature produced very variable results, even across data sets created by the same person, suggesting that the ANN would find a good solution very quickly and so this value could potentially be dramatically reduced.

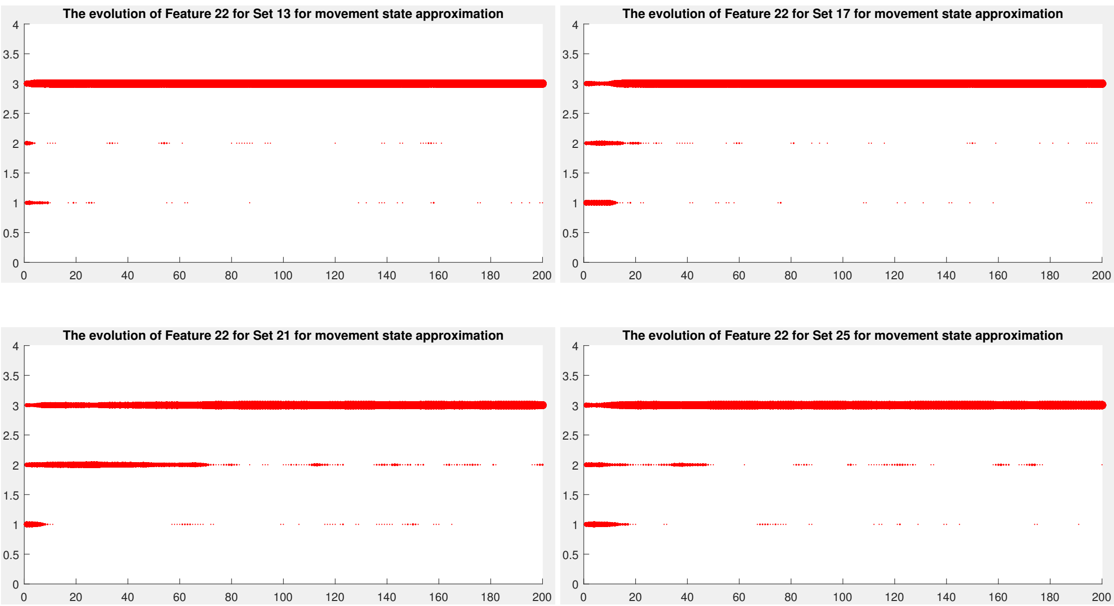


FIGURE 5.21: The evolution of feature 22 - Number of layers in the ANN - for a sample of sets

Conversely, for feature 22, the number of layers in the ANN, the evolution produced the same result in every case as shown in Figure 5.21.

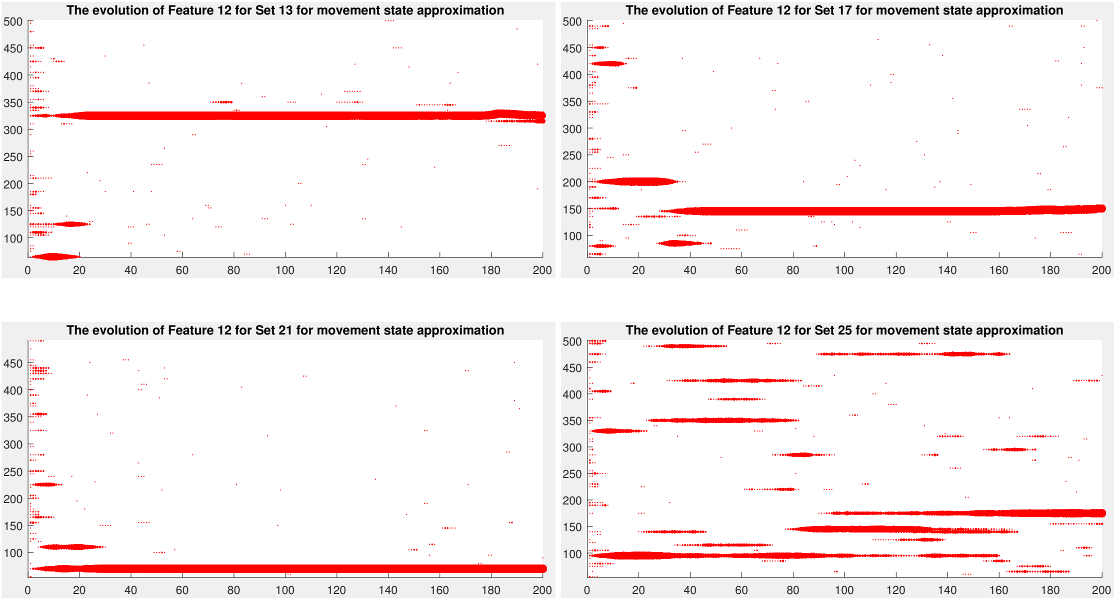


FIGURE 5.22: The evolution of feature 12 - Pressure 1 Minimum- for a sample of sets

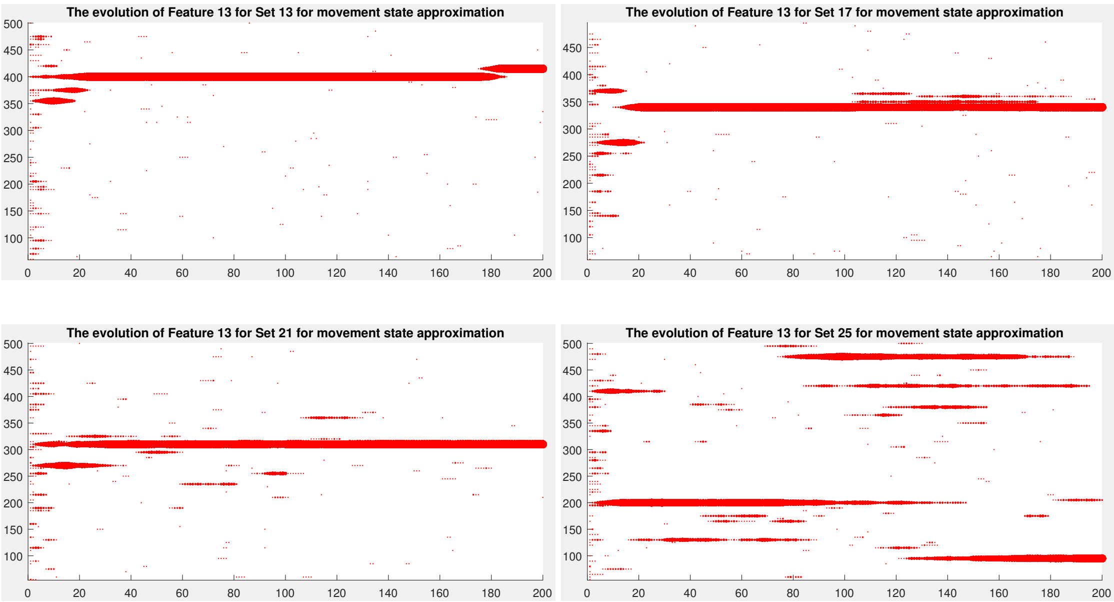


FIGURE 5.23: The evolution of feature 13 - Pressure 1 Maximum- for a sample of sets

Figures 5.22 and 5.23 show a sample of evolution plots for the minimum and maximum pressure for the pressure feature.

There are nearly a thousand of these plots and so the evolution of all the genes for one set of data have been shown in Appendix F and the evolution of one gene for all the sets of data has been shown in Appendix G.

5.5 The Gene Settings for the Best Individual for Each Data Set

Tables 5.8 and 5.9 show the best individual for each data set after 200 generations for both Movement State Approximation and Speed Estimation.

As can be seen, the accelerometer features were hardly used at all on the Movement State Approximation runs and this is not surprising as they are predominantly helpful for Speed Estimation.

This is further demonstrated in the evolution plots in Figure 5.24 where the evolution of this feature for Movement State Approximation is shown on the left and the comparable evolution for Speed Estimation is shown on the left for 2 volunteer runs.

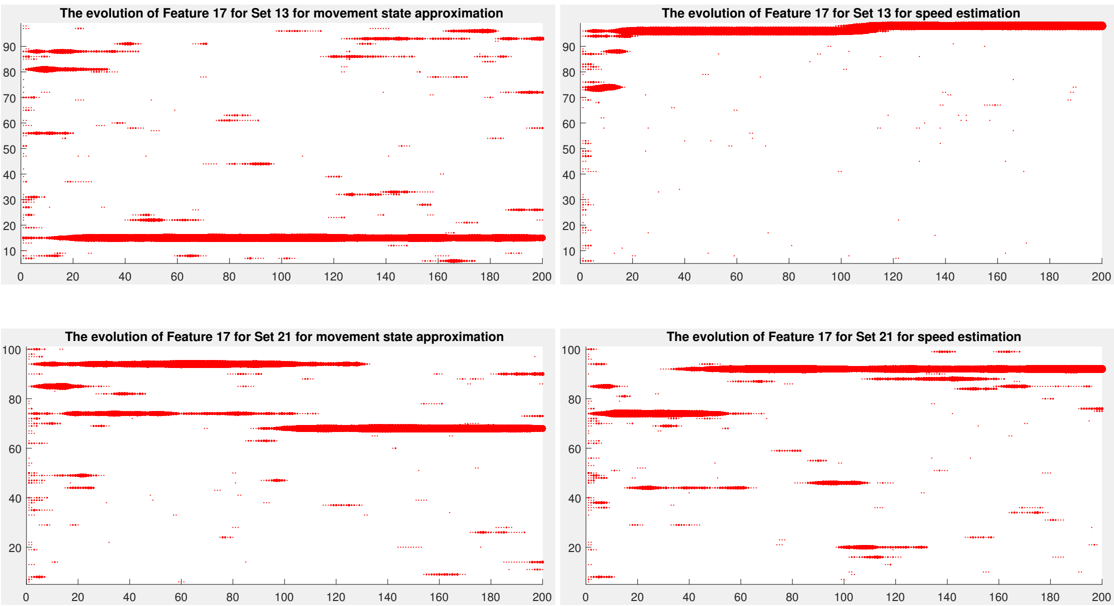


FIGURE 5.24: The evolution of feature 17 - Accelerometer feature calculation - for a sample of sets

Figure 5.25 shows the evolution of the gene used to choose whether or not to use these features for the same two volunteer runs showing, in both cases, that the feature was chosen for Speed Estimation but was not chosen for Movement State Approximation.

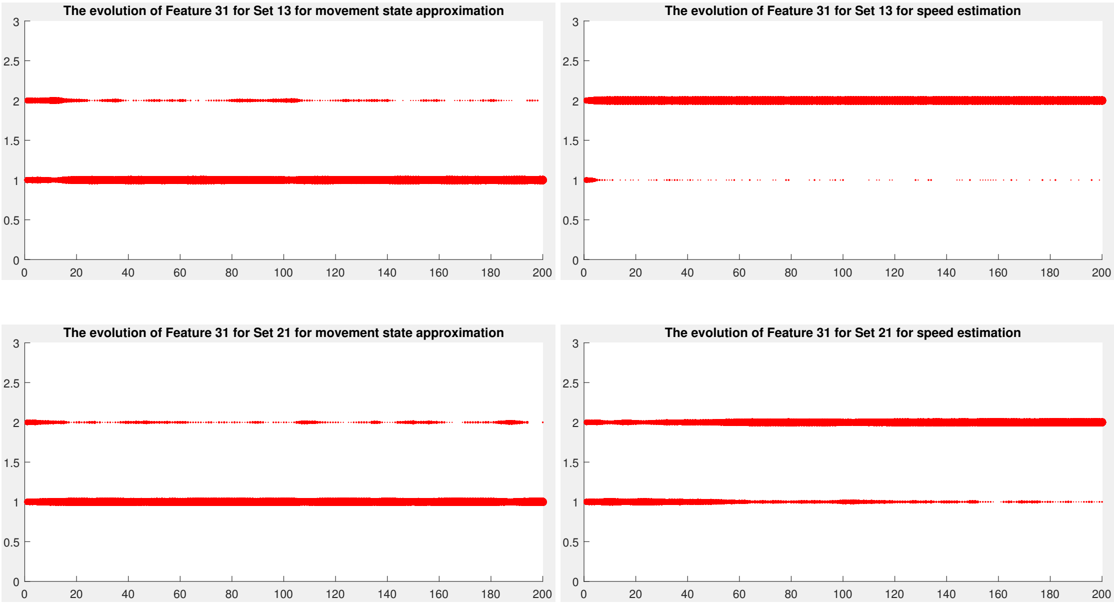


FIGURE 5.25: The evolution of feature 31 - Use Accelerometer 1 - for a sample of sets

More surprising is that the pressure sensor features are used for Speed Estimation, despite them being most useful for determining Movement State Approximation as shown in Figures 5.26 and 5.27.

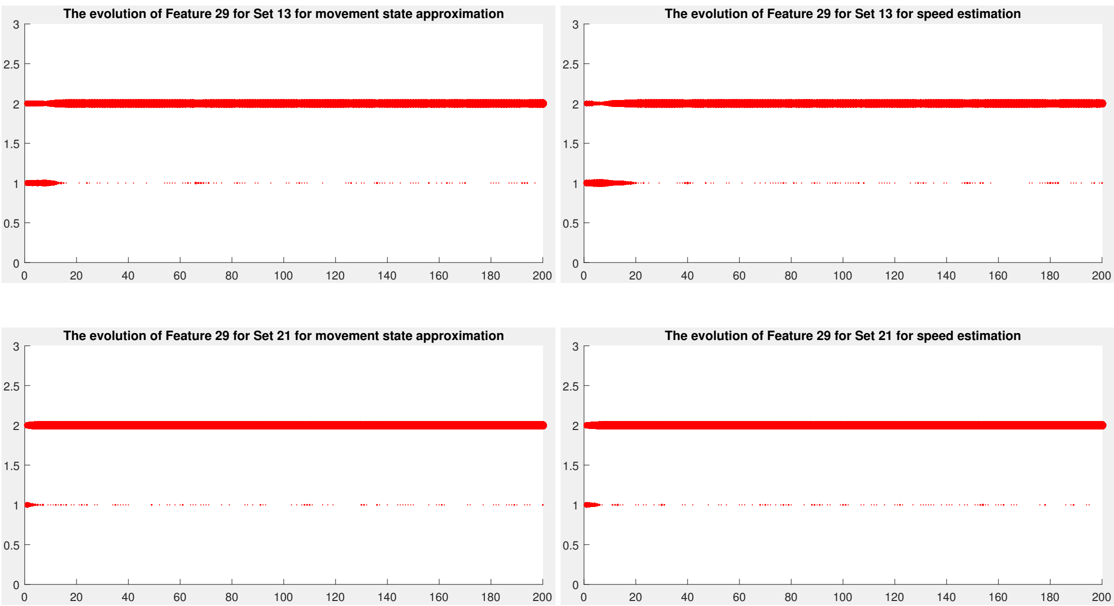


FIGURE 5.26: The evolution of feature 29 - Use Pressure Sensor 1 Feature - for a sample of sets

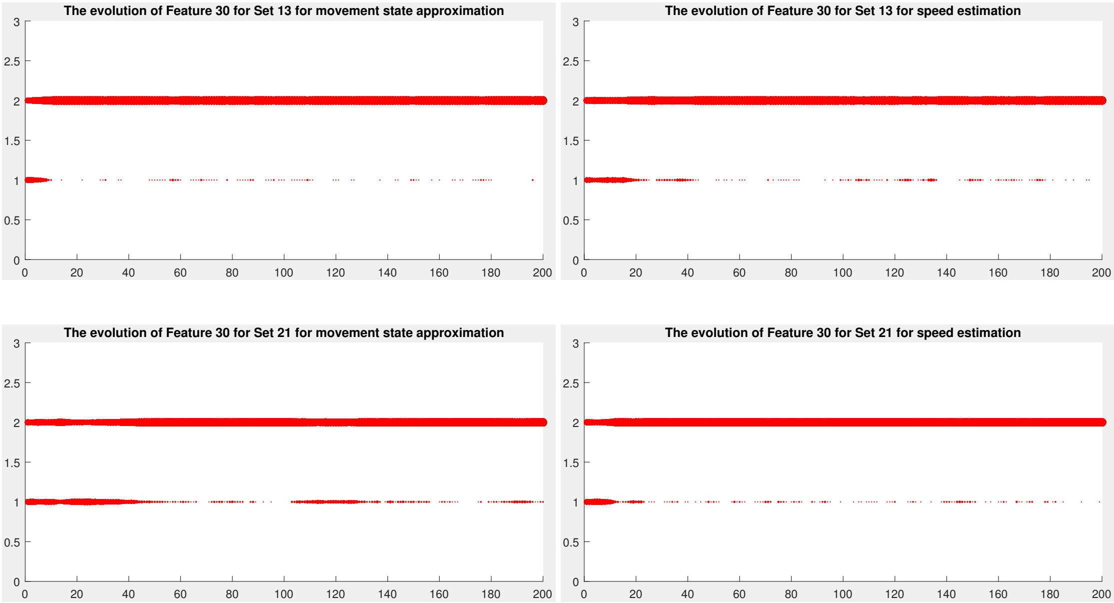


FIGURE 5.27: The evolution of feature 30 - Use Pressure Sensor 2 Feature - for a sample of sets

5.6 Putting Data Sets Through Other Networks

A further series of tests was carried out whereby the best network created for each data set was loaded into matlab and then every other dataset was passed through it.

Figures 5.28 - 5.31 shows some of the results for the best network found for dataset 21.

Figure 5.28 shows the result of passing dataset 21 through the network and, as would be expected, the network produces a very close approximation of the speed.

Figures 5.29 - 5.31 show the results of passing datasets 22, 23 and 24 through the network for dataset 21. Datasets 22, 23 and 24 were created by the person who created dataset 21 and, as can be seen, do not produce good results.

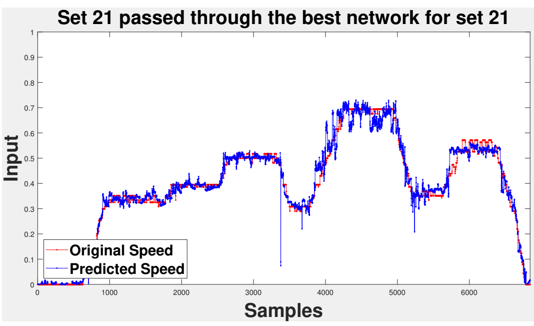


FIGURE 5.28: Set 21 data passed through set 21 network

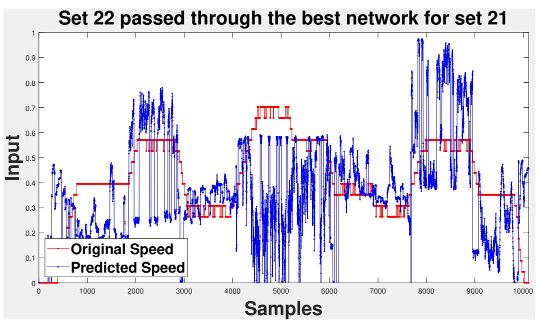


FIGURE 5.29: Set 22 data passed through set 21 network

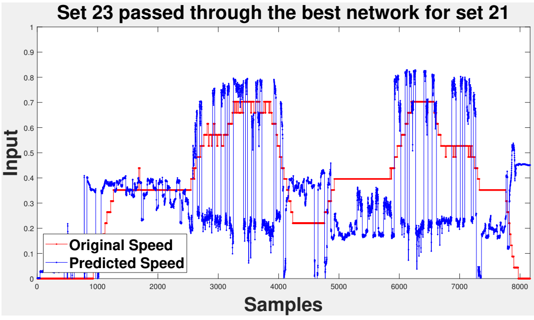


FIGURE 5.30: Set 23 data passed through set 21 network

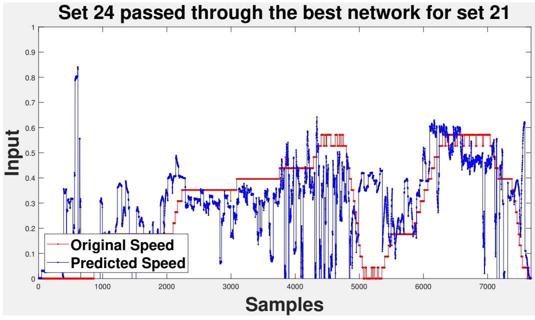


FIGURE 5.31: Set 24 data passed through set 21 network

Figures 5.32 - 5.33 show the results of passing datasets 15 and 16 through the network for dataset 21. Datasets 15 and 16 were created by a person of the same sex and fitness level as the person who created dataset 21. This appears to produce a good level of similarity to that produced by the original volunteers other runs.

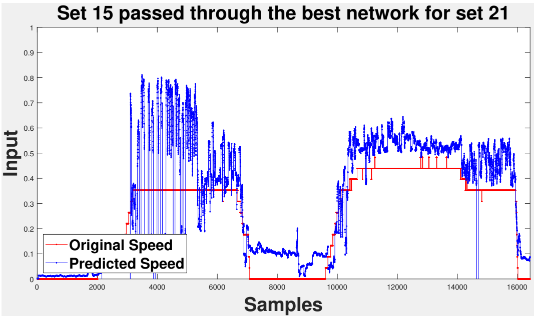


FIGURE 5.32: Set 15 data passed through set 21 network

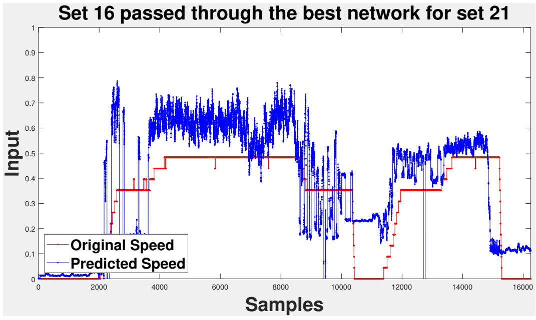


FIGURE 5.33: Set 16 data passed through set 21 network

Figure 5.34 shows the results of passing the dataset created by the person able to run the fastest through the network for dataset 21 and Figure 5.35 shows the results of passing the dataset created by the amputee through the network for dataset 21. As can be seen, both of these produce results that would be completely unusable.

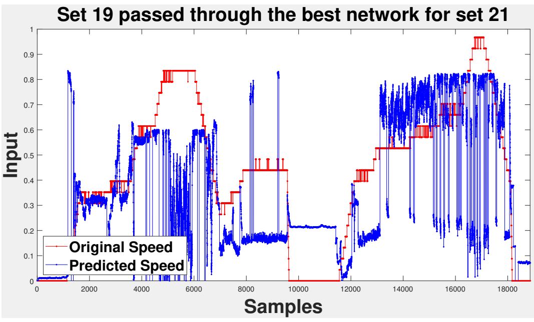


FIGURE 5.34: Set 19 data passed through set 21 network

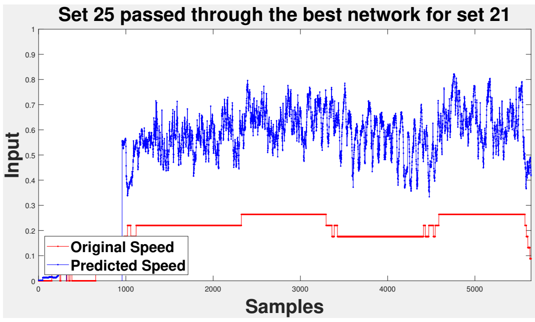


FIGURE 5.35: Set 25 data passed through set 21 network

A full list of all these graphs is shown in Appendix H.

5.7 Summary of Results

The results outlined in this section have shown that the original hypothesis has been proved. This has been shown by the fact that:

- The results of the ANN have been greatly improved by introducing the GA to tune the parameters
- Each volunteer needed different settings and different features to be included in the inputs to the ANN to produce the best results for them
- The GA successfully evolved each gene for each individual
- The GA was able to include features in the final selection that a human may not have considered useful thus showing its usefulness
- A network that has been optimised for one volunteer does not work well for another

Chapter 6

Conclusions

The work carried on in this thesis involved the use of artificial intelligence to improve the control of prosthetic legs. In particular, it focused on the identification of the users movement state, walking and running, and the speed of theses movements.

Previous research [4, 5] had shown that an ANN can successfully distinguish between walking and running and determine the movement speed of an individual with a certain degree of success. However, tuning the parameters for both the input features of the ANN and the ANN itself became too onerous a task to be achieved through the trial of every possible permutation. The purpose of this research was to explore the use of a genetic algorithm (GA) to tune these parameters, based on an individual's needs and body while walking and running.

In this investigation, data from a wearable gait lab was collected in order to classify the movement state and approximate the movement speed of subjects. Using:

- One EMG Sensor
- Six pressure sensors, one under the heel, toe and ball of each foot
- Four accelerometers, one on the thigh and calf of each leg
- A Wheel Sensor

Unique features have been presented which have then been combined with signal processing, a GA and ANNs for this purpose.

The movement state and speed are required for the next generation of control strategies for prosthetic lower limbs. Although there is currently a considerable level of research being conducted on the detection of movements in prosthetic limbs, this study predominantly focused on the detection of phases in the walking gait [46, 118], or in movements such as stand to sit [46, 119].

6.1 Introduction

Previous work has shown considerable success in distinguishing the movement mode (standing still, walking or running) and the speed of movement. However, when experiments were conducted with different volunteers it was found that the same settings did not work for each person.

Introducing the GA allowed many different parameters to be trialled, in many different combinations, using only those that gave successful results to move forward, and thus allowing highly optimised combinations to be used for each individual. The results of this GA show tFhat each individual requires different parameter settings and different features to achieve an optimised classification system for them.

This work used a series of sensors built into a wearable gait lab which was specifically developed for the purpose. The sensors are small and light and so could easily be embedded into a prosthetic limb or into a wearable harness for the user to have in a belt pack.

6.2 Improvement on Previous Work

One of the initial issues in the previous work was that during training the speeds predicted by the ANN gave good results but when the ANN was then tested with new data the performance level significantly degraded.

However, this new work has shown major improvements on the previous work including the ability to predict the higher speeds and change in speeds more accurately as outlined in Section 5.1.1. This is beneficial for improving prosthetic limb control as the settings of the limb need to change for different speeds and so any delay in detecting a change in speed or higher speed will impair this adjustment.

The previous work also showed how difficult and time consuming the task of optimising the parameters manually was and this work has improved on that by allowing the GA to find the correct parameters for each individual. This gives the potential for the control strategy for a prosthetic limb to be personalised to each individual.

6.3 New Findings From This Work

In this work, a GA has been added to allow suitable parameters for each individual to be determined. This extension included the introduction of a series of genes that turned on or off each feature depending on it's usefulness to the user. This is a unique method of determining feature use as far as the author is aware.

The introduction of the cross validation and randomisation has dramatically increased the ability of the ANN to define detail when estimating the speed the user is travelling at. This will allow more accurate and timely control of a prosthetic limb. This has the potential to significantly improve the quality of life of people using prosthetic limbs by allowing the control parameters of the limb to be tailored to each individual person's needs. It would also allow the parameters to be re-tuned as needed as the individual's needs change during recovery from surgery or increased ability as rehabilitation progresses.

6.4 Analysis of Results

The results have shown that the GA tuned ANN can estimate the speed and movement state of the user with greatly increased accuracy over the previous work. It also distinguishes the correct genes and gene settings for each individual.

The gene system allows the correct feature parameters and genes to be selected for each individual and this would allow for a prosthetic limb control strategy to be tailored more accurately to the individual.

Not only would this work for prosthetic limb users it would also have the potential for working with orthotics to help people with disabilities. For example, it could assist someone who has lost partial use of their limbs following a stroke by supporting their movement. It could also be used for someone with cerebral palsy both to assist their walking gait and even to improve and correct it to allow freer movement.

Novel and key connections have been found between some features and further exploration of co-dependencies could be profitable here such as the relationship between certain setting values and the choice of whether or not to use that feature.

Conversely, some features have been found not to be useful at all including the choice of the number of layers in the ANN.

Of particular interest is the results of putting one individual's data through another individual's well tuned network. This has shown that each individual needs their own, tuned network to suit their own requirements.

6.5 Wearable Gait Lab

While typically prosthesis movement and walking gait movement is analysed in a laboratory, the wearable gait lab presented in this thesis allows the users movements to be captured anywhere off-site. This allows for more natural movement to be analysed.

In this work a wearable gait lab has been developed which allows the wearer to run on a treadmill with minimum inconvenience. This then allows data to be gathered from a variety of sensors built into the harness while the wearer carries out different activities at their own speed and in their own time on the treadmill in a more natural way than that gathered in the laboratory. This data can be gathered continuously over an extended period of time allowing for a significant quantity of data to be gathered which can then be analysed off-line. The proposed future addition of highly accurate GPS monitoring would increase the effectiveness of the wearable gait lab by removing the unnatural movement of the treadmill.

6.6 Feature Development

Based on data collected from the wearable gait lab, a number of novel features have been identified, used and tested throughout this work, and several of these output features have been shown to have a close connection to the desired output. These included the accelerometer jerk feature and the pressure crossover feature.

The accelerometer jerk shows a close correlation to the speed of the subject, and requires a window of only two samples. Therefore, it is able to react to changes in the speed of the subject rapidly. While the pressure sensor feature also has a close correlation to the movement state of the subject, and requires no window of samples, it is able to quickly respond to changes in movement.

It has also been interesting to note how the parameters for these features have varied and how the GA has chosen to turn the features on and off when an unsuitable value has been chosen for a given parameter.

6.7 Movement State Approximation

Movement state approximation gives a simple, single value output based on whether or not the system believes the user is standing still, walking or running. The purpose of this output is to let the prosthetic limb know what swing and resistance settings to use as these differ significantly between these 3 activities. The previous work was able to give good results for this approximation and this work has only slightly improved on that. However, the accuracy with which the system can determine the movements state suggests that it would be possible to make a prosthetic limb change state automatically rather than needing a manual button press from the wearer.

6.8 Speed Estimation

One of the biggest improvements on the previous work is the accuracy with which the system can predict the speed the user is moving at. This, combined with the Movement state approximation suggests that the prosthetic limb would be able to adapt/change between running slowly, walking quickly and then standing still.

6.9 Artificial Neural Network

The use of neural networks for the classification of signals gathered from the body is a long established and successful technique [120–122].

The research carried out prior to this work demonstrated that the application of an ANN was well suited to this work [4, 5]. However, this work has extended that research to show that the usefulness of the ANN can be improved and extended by the addition of the GA.

Using an ANN in this situation brings three potential benefits for the tuning of a prosthetic leg control strategy.

Firstly, it will allow the parameters being passed to the leg to be tuned to suit the individual.

Secondly, it will then be able to determine which parameters to pass to the leg in which situation by classifying what the user is currently doing or how their movement is changing.

Finally, as the user's ability changes following rehabilitation, therapy or the adopting of a new sport, it will allow the parameters to be tuned again to keep pace with the user's activity.

6.10 Genetic Algorithm

As the previous work [4, 5] had shown promise with hand tuned parameters this work added the extension of optimising the parameters for both the features being fed through the ANN and for the ANN itself with a GA. Optimisation of an ANN with a GA has been used in other situations [123, 124], however, this work has brought in an innovative method of selecting the features to be used by allocating a single, binary gene to each feature which can turn it on or off.

Through this GA optimisation it has been found that each individual needs different parameter settings and different combinations of genes. It can also be seen that the values chosen in each case are dependent upon each other.

The gene methodology used would easily allow for further genes to be added if required in the future thus allowing the system to be expanded.

6.11 Classifications for Each Individual

As outlined above, this work has shown that each individual needs different features and different parameter settings for those features to allow their movement state and speed to be approximated.

It has also shown that the GA will settle on similar values for the parameter settings for different data sets from the same individual thus showing that it is finding the optimal settings for that person.

6.12 Further Work

The wearable gait lab described in Section 4.2 proved to be extremely effective in allowing a volunteer's movements to be tracked while standing still, walking and running a treadmill. This lab, coupled with the controllable treadmill speed, allowed clear data to be gathered which could then be used as both the inputs and outputs for the ANN.

However, the use of the treadmill clearly limited the movements of the volunteer to walking or running in a straight line. It also introduced unnatural actions around the acceleration and deceleration points caused by the change in speed of the treadmill.

6.12.1 Proposed future control system

The proposed system by which the output from the neural network is used to control a real prosthetic limb is to provide the data (from the ANN) for a look up table. The look up table would then be used to convert the real-time sensor readings into real-time control outputs for both allowed swing and resistance to the prosthetic leg.

6.12.2 Wearable Gait Lab With GPS System

The limitations caused by the use of the treadmill could be overcome by the use of the Swift Piksi Multi GNSS Module [125] highly accurate GPS system which allows accurate location within 10 cm by using two GPS units that have been synchronised. One remains stationery and the offset to the other can then be calculated with a high level of accuracy.

This system would allow a volunteer to move more naturally and for their speed of movement to be captured in real time.

6.12.3 Synchronised Video and Audio Capture

A further improvement would be to add video and audio capture to be synchronised with the data. Simple techniques could be explored whereby the volunteer makes a specific movement and sound at the start of a trial that will allow simultaneously recorded audio and video to be synchronised with the data from the wearable gait lab. This would then allow for other activities to be analysed such as standing to sitting and ascending and descending stairs.

6.12.4 Improvement of GA and Features

An improvement to the GA could be considered whereby known dependent genes, such as the maximum and minimum pressure for the pressure sensor feature, could be tuned in conjunction with each other rather than separately.

The success of the gene evolution and the way in which it has chosen individual features and parameters for each individual suggests that it could be possible to develop more genes including ones tailored to the individual. For example, the EMG based features may work differently depending on the length of residual limb of an amputee and so more features may need to be developed. It may also be possible to develop different features based on the fixation method of the prosthesis as those attached by sockets are known to behave differently to those attached by osteointegration.

Further work with amputees would allow a greater volume of data to be gathered and this would allow further features to be developed and better tuning of the ANN.

6.12.5 Extension to Other Activities

This work has concentrated only on walking and running in a straight line because the user was restricted to moving on a treadmill so that the speed could be accurately recorded.

By using the other activity capture methods described above it is possible that many other activities could be incorporated such as cycling, skiing etc. It is even possible that the system could become self learning so that prolonged activity using a regular sequence of movements could be classified.

6.12.6 Wireless Connection

Many commercially produced prosthetic legs already make use of Bluetooth connectivity. In the main this is to allow setting up the parameters of the limb. However, the Linx leg system, made by Blatchford, uses Bluetooth to allow the knee and ankle to communicate and adjust together to compensate for varying terrain [126]. For example, if the ankle detects that it is opening further than normal it can alert the knee to the fact that the wearer is probably going downhill and that the knee should stiffen up.

Using wireless connection in conjunction with the system proposed in this work would allow both the knee and ankle to benefit from input from all the sensors in real time as processed by the ANN.

6.12.7 Learning App

A smartphone app could be considered to allow the learning of new activities via a Bluetooth connection. The user would tell the system they wanted to define a new activity, such as cycling, then perform the activity while the system tries different settings for the leg. Feedback through the app could then be given to say whether or not the settings chosen by the system are appropriate.

To protect the user from injury an emergency setting would need to be defined such as forcing the leg to go into supportive standing mode.

6.13 Critical Analysis

While this work has proved to be successful there were areas of the research that could have been improved.

6.13.1 Creation of New Hardware

The desire to move on to another iteration of hardware meant that samples were taken quickly from several volunteers and then the equipment dismantled ready to create the new version of hardware. This new version of hardware then proved too complex to create within the time available and so the only data available was that taken from the original equipment.

This set up has proved to be more than adequate to carry out the research but in hindsight it would have been better to keep the equipment intact until the initial analysis of the data had been done to allow for further samples to be taken.

6.13.2 Choice of Software

This work was carried out in Matlab to make use of the ANN toolbox provided with the software. However this meant that the processing of each individual set of data was slow, up to 2 days per full run. A better method might have been to write an individual ANN in C++ or other high level language so that the processing of the data could be optimised for speed.

6.14 Summary

This work was more successful than anticipated with clear evolution of the genes taking place which quickly improved on the previous work and went on to find the optimised parameters for each individual

The work also showed that each individual needed significantly different features and this will lend itself well to creating bespoke control strategies for prosthetic limbs. The speed that a well trained ANN can potentially make decisions about the current movement state and speed is ideal for this work as is the fact that the Control strategy can be adapted

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Appendix A

Published Papers

State Detection from Electromyographic Signals towards the Control of Prosthetic Limbs

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Abstract — This paper presents experiments in the use of an Electromyographic sensor to determine whether a person is standing, walking or running. The output of the sensor was captured and processed in a variety of different ways to extract those features that were seen to be changing as the movement state of the person changed. Experiments were carried out by adjusting the parameters used for the collection of the features. These extracted features where then passed to a set of Artificial Neural Networks trained to recognise each state. This methodology exhibits an accuracy needed to control a prosthetic leg.

Index Terms — Artificial Neural Network, Electromyographic Sensor, Feature Extraction, Pattern Recognition, Prosthesis

I. Introduction

The development of effective and functional prostheses has become increasingly important. This is in part due to the rise in injuries caused by the number of conflicts in the world and also due to the improvements in medical science meaning that people are more likely to survive limb threatening injuries [1].

There are many problems experienced by those trying to produce prostheses to emulate a real leg which are slowly being resolved. However, one particular problem still persists, the way in which the unit reacts to changes in the movement state of the wearer. Generally this change in state requires a manual command from the wearer either through manipulation of the prosthetic or through a remote control [2], [3].

The purpose of this research was to examine ways in which this area could be improved and the use of an electromyographic (EMG) sensor on the surface of the prosthesis wearer's skin was explored. Signals from the EMG sensor were recorded while a subject was standing still, walking and running. These recorded signals were then examined to extract a series of features including the average, the maximum signal height, the width of the last cluster of signals and the gap between the last two clusters. Various artificial neural networks (ANNs) were then trained to recognise each state.

This paper is divided into five sections. A literature review is presented in section two, the methodology is presented in section three and experimental results are given in section four. Final conclusions are drawn in section five.

II. Literature Review

There are two main ways in which computational intelligence can be used for prostheses control. The first is in interpreting signals from the wearer to determine what movement they are making or are about to make. These could be done by using pressure or movement sensors within the prostheses [2], [3] or EMG sensors on the surface of the skin. The second is in controlling the actions of the limb and there is overlap between the development of prostheses and of robots and exoskeletons. In both cases the artificial limbs need to move and balance like a human limb to be successful. This area of control can be split into two. The first being simple pattern recognition to determine the current state of the prosthesis from the incoming signals. This could be a simple command to open or close a hand or it could be a more complex output controlling individual fingers. The second is in the control of the entire walking gait of e.g. a bipedal robot.

A. *Gathering EMG signals*

Signals from an EMG sensor have previously been used to control a prosthetic arm as early as 1984 [4]. Research has been done into the fact that the residual limb can still give the signals required to control the missing part of the limb and the challenges of doing this are discussed in [5]. One of the main challenges is that each person and each type of step produces different signals at different times making pattern recognition difficult. Another challenge is that the signals that reach the surface mounted EMG sensor have to pass through other muscles, tissue and bone, all of which will have an effect upon the signal, and this is discussed in [6].

Another consideration is how much of the residual limb and muscle remains and also how far this muscle has atrophied. Often, amputees have to work hard to build these muscles back up so that the residual limb becomes useful again. In some cases this development has gone even further and [5] describes work that has been done with upper limb amputees to transfer the nerves previously used to control the amputated limb to other muscles so that they can be used to stimulate the prosthesis. Based on this, it is suggested that this technique could also be used for lower limb amputees.

In [7] multiple sensors were used over the main six muscles of the thigh. While this gave excellent results it is unlikely that mounting this number of sensors regularly would be practical.

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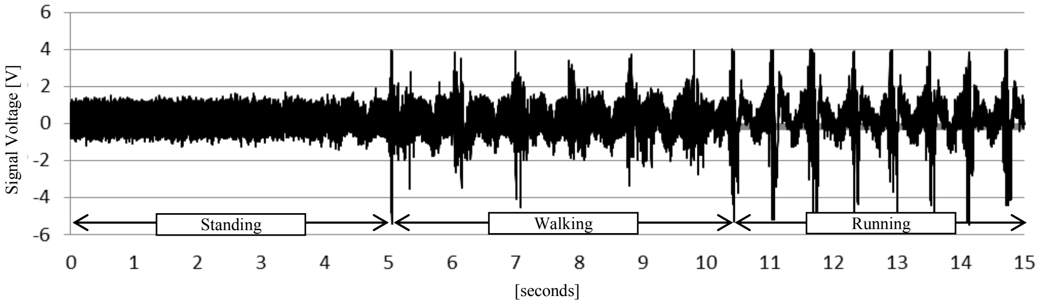

Figure 1 – A sample trace from the sensor showing the output during standing, walking and running

However, Cheron et al process the data from these sensors to give relevant angles for each part of an entire limb rather than creating a usable prosthesis that will function in real-time.

As well as the control of prostheses, the possibility of using EMG signals for teleoperation has previously been considered [8], [9]. This allows a human to control a remote limb where the environment in which the limb needs to operate would be hostile to a human. It is suggested that using EMG sensors for control is more intuitive and less fatiguing than traditional manual control methods such as joysticks. Another form of remote operation is discussed in [10] where the authors have used EMG signals to directly control an exoskeleton. This has potential for disabled people with paralysis of the limbs.

B. Feature Extraction

The information that comes from the EMG sensor, shown in Figure 1, is in the form of a signal that an ANN would not easily be able to recognise. It is therefore beneficial to extract relevant features that distinguish one movement state from another. In [11] this is described as the "main kernel of classification systems and it is essential to the motion command identification". Park and Lee highlight that it is difficult for one feature to reflect the overall state of the signal and so several different features are required.

This research looks at using a variety of features collected over a number of samples and the relevance of the size of this number is discussed. Two factors that need to be taken into account when choosing this number are the sampling frequency and the number of movements being made. Another technique used to extract features is filtering [6]. Most papers agree that the extraction of data from the signal in a timely fashion is one of the hardest aspects of the process.

C. Pattern Recognition

Once the features have been extracted from the EMG signal they need to be used to distinguish between the different states. This process involves looking at the patterns within the signal features and then training a computational intelligence system to recognise and separate these patterns. This can be done by using e.g. fuzzy mapping functions [11] or a variety of ANNs [6], [9] and [12].

Finding a relationship between the features and the different states or patterns can be achieved in a variety of ways. In [13], it is discussed that the amplitude, magnitude and intensity of the EMG signal has a relationship with the force and position of the limb. However, rather than using this data for real-time control of a limb, the authors use it to predict how the user is walking and to simulate the walking gate from the EMG signals through an ANN.

D. Controlling a limb or prosthesis

Computational Intelligence has been used to control prosthetic limbs in a variety of ways. In [7] the outputs from the EMG are passed through a dynamic recurrent neural network (DRNN) to control all three sections of a virtual limb on screen. The outputs from the DRNN are in the form of angular velocities for the hip, knee and ankle joints.

A true control system is discussed in [14] where the authors have studied the intricacies of walking. They use a feedforward neural network to overcome the limitations of rule based control systems which are unable to take into account changing demands and terrain. This produces a simulation of a prosthesis which is very effective but not real-time. The authors of [15] look at using a real-time neural network to control a biped walking robot. This uses a cerebellar model arithmetic computer (CMAC) neural network to control the walking gait of the robot using sensors built into the legs to give feedback.

The Plymouth Hand [6], [12] and [16] project has extensively researched the use of an EMG signal to control a prosthetic hand. The authors describe how a single EMG signal is gathered, passed through a series of filters and then fed into a neural network which has been trained to recognise a series of positions for the hand.

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III. METHODOLOGY

An EMG sensor can pick up the signals sent by the nerves through the body to control the muscles. The EMG sensor used for this research consists of:

- A Motion Lab Systems MA 317 A300 A3 Preamplifier
- An amplifier circuit to further increase signal levels
- A Data Translation DT9801 Multifunction USB Data Acquisition Module
- Data Translation DT Chartrecorder software

The performance of EMG based pattern classification can deteriorate due to inevitable disturbances to the sensor interface. Therefore, it is critical to locate, within the upper part of the leg muscle of a trans-femoral amputee, the positions which provide the best EMG signals. This was one of the key aims of this research.

Positioning the sensor proved to be quite challenging. It was found that the sensor needs to be held on securely and in precisely the correct position. A trainee doctor was consulted and following reference to two texts, [17] and [18], he advised trialling the sites shown in Figure 2.

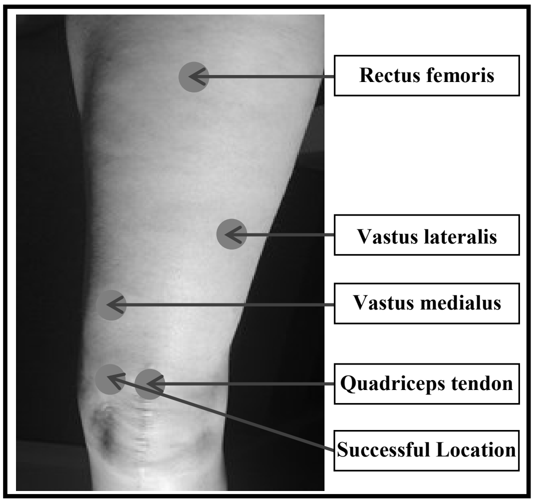

Figure 2 – Sites trialled for the location of the sensor and the final successful and recommended location

A. Signal Capture

The setup for the DT9801 Data Acquisition Module allows for many changes to be made to the parameters including the units, offset, range and pre-set triggers. However, for the purposes of this research only the sampling rate was altered between 200, 500 and 1000 Hz.

Figures 3, 4 and 5 show the Sensor output in different states. As can be seen in Figure 3, the signal oscillated between plus and minus 9v when there was no contact with the leg. Figure 4 shows the Sensor output when connected to the leg but without any movement. Finally, Figure 5 shows the Sensor output when movement was detected.

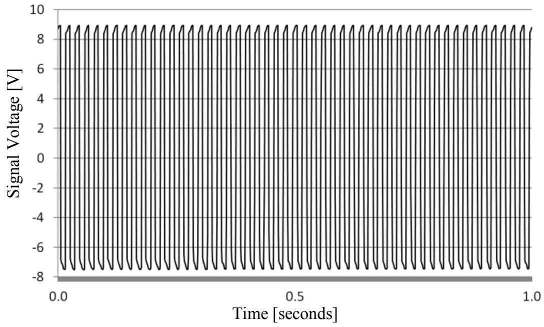

Figure 3 - Sensor output without contact with leg

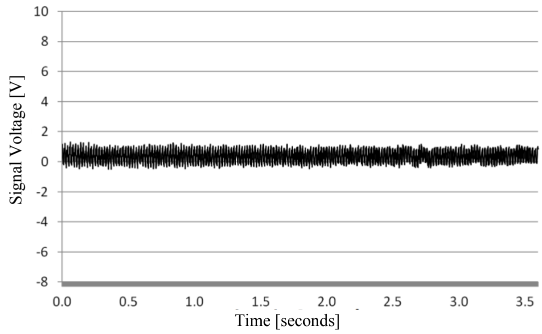

Figure 4 - Sensor output with contact with static leg

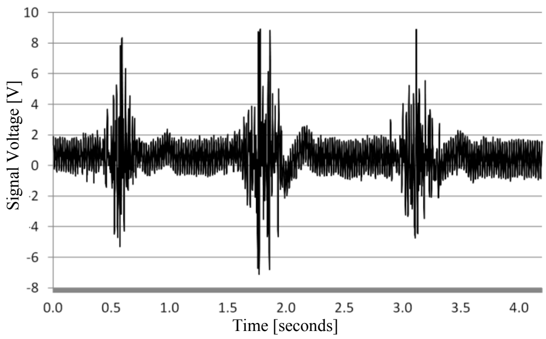

Figure 5 - Sensor output with contact with moving leg

B. Extraction of Features

The raw signal from the sensor was recorded and then passed through a simple filter whereby the last three absolute signals were multiplied together and averaged. The resulting output was examined to determine what features were changing in each state. The extraction of these features was trialled with the original signal, the absolute signal and the spikes of the signal above a certain height. The extracted features are outlined below.

Maximum sample (MAX) - The maximum sample over the last SS_Max samples was acquired where SS_Max is the buffer size used for this calculation.

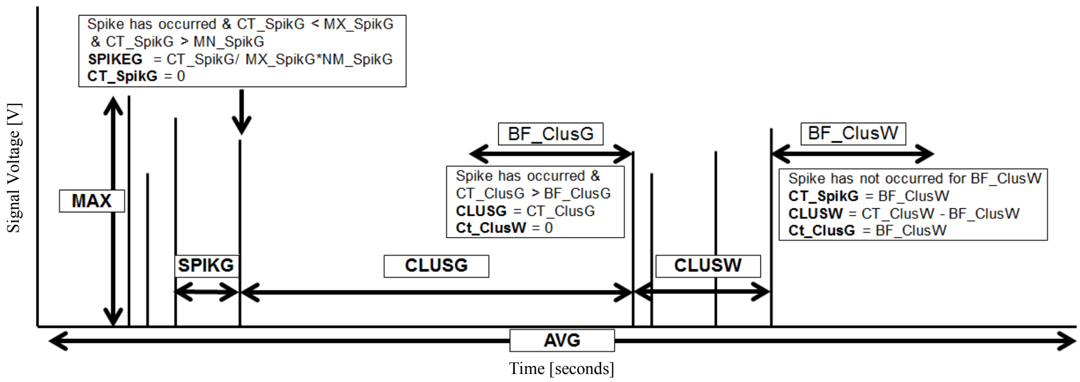

Figure 6 – This diagram shows the method used to calculate each feature and in particular shows how the buffers BF_ClusG and BF_ClusW are used to determine the start and end points of the features CLUSG and CLUSW. Abbreviations of these techniques are explained in more detail in Section II.B

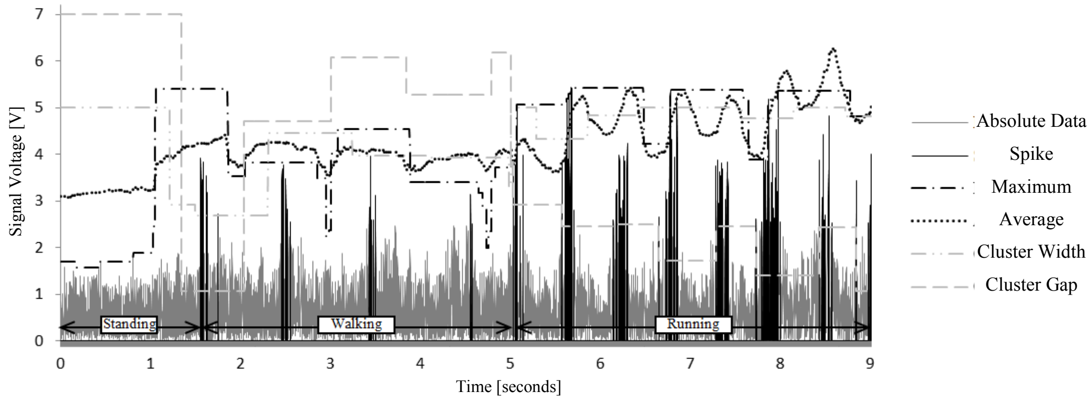

Figure 7 – Sample EMG absolute output data showing the positions of the extracted spikes and traces for the four successful features of Maximum, Average, Cluster Width and Cluster Gap

Average of samples (AVG) - The average of the signal was calculated by summing all the samples over the last SS_Avg samples and placing them in a buffer called BF_Avg.

Cluster Width (CLUSW) - While observing the differences between the samples taken during walking and running it became clear that the width of the cluster of spikes above a certain height, SZ_Spike, was changing. This feature is found by using CT_ClusW to count the time between the first and last spike of a cluster. A Spike is deemed to be the last one in a cluster if a certain number of samples, BF_ClusW, have passed. This means that CLUSW has to be calculated retrospectively. CLUSW is limited to a value of MX_ClusW and normalised using NM_ClusW

Cluster Gap (CLUSG) - This feature is determined by calculating the time between the last spike of the last cluster and the first spike of the next one within a certain number of samples. The Feature Extraction Parameters BF_ClusG, MX_ClusG and NM_ClusG were used in the same way as for CLUSW.

Table 1 - Typical feature extraction parameters used for different sampling frequencies

Parameter	Sampling Frequency 1000	500	200	100	Description
Sample_set	2000	1000	400	200	Maximum sample set
SS_Max	800	400	160	80	Sample set for MAX
SS_Avg	800	400	160	80	Sample set for AVG
BF_Avg	0	0	0	0	Buffer to collect Average samples
NM_Avg	7	7	7	7	Normaliser for Average
MX_SpikG	40	20	8	4	The max value a spike gap can reach
MN_SpikG	10	5	2	1	The min value a spike gap can reach
SZ_spike	2.5	2.5	2.5	2.5	Height of the spike
NM_SpikG	9	9	9	9	Normaliser for SPIKG
BF_ClusW	300	150	60	30	Required Spike Gap for CLUSW
MX_ClusW	300	150	60	30	The Max value for a Cluster Width
NM_ClusW	9	9	9	9	Normaliser for CLUSW
BF_ClusG	500	250	100	50	Gap between spikes for CLUSG
MX_ClusG	1000	500	200	100	The Max value for a Cluster Gap
NM_ClusG	9	9	9	9	Normaliser for CLUSG

A number of parameters were used for each extracted feature and these are shown in Table 1. This table also shows typical values for each parameter at each sampling frequency. The way in which the feature extraction parameters were used to calculate the features is shown in Figure 6 and the resulting features are shown, superimposed on the signal in Figure 7.

The captured EMG signals and the extracted features where combined into a single text file along with the correct "movement state" value. The "movement states" were 0 for standing, 1 for walking and 2 for running.

C. Artificial Neural Network for State Detection

In order to process these signals with an ANN it was necessary to add a "movement state" to each sample taken. The states used were 0 for standing still, 1 for walking and 2 for running. The movement state was added to the signal by simply recording the required state for a set period of time and then adding the state marking by eye afterwards.

This is a preliminary work which aims at having a sliding scale of outputs to cater for different levels of running/walking not just discrete states. Therefore an ANN was used to distinguish between the movement states based on the extracted features. Other techniques, including Bayes could be used in future work.

Two ANN implementation methods were used, the first used bespoke C++ code to create the ANN and process the data, the second used the MatLab artificial neural network toolkit for further investigation.

For this preliminary work, feedforward backpropagation ANNs with one or two hidden layers have been used. Hidden nodes used hyperbolic tangent sigmoid transfer functions, and the output nodes employed linear transfer functions. The Levenberg-Marquardt backpropagation learning [19] was used to train the ANNs. All feature vectors were tested individually and as a group and were tested on ANNs containing between one and five hidden nodes in one or two hidden layers thus giving 5 x 5 x 5 ANNs.

In addition, experiments were also carried out by passing the recorded signals through a series of ANNs in Matlab. A feedforward backpropagation network was used with the default transfer function of tansig. The training function was gradient descent with momentum and adaptive learning rate backpropagation (traingdx), the weight/bias learning function was gradient descent with momentum weight and bias learning function (learngdm) and the performance function was the mean squared normalized error performance function (mse).

Experiments were carried out with different combinations of input and output neurons, extracted features and movement states. The input and output combinations trialled included 10,5, 2,3, 7,5 and 7,3.

The extracted features trialled consisted of various combinations of MAX, AVG, CLUSW, CLUSG and SPIKEG. These features were trialled in various combinations of 2's, 3's and 4's.

Attempts were made to differentiate between the movement states of standing, walking and running in various combinations.

IV. RESULTS

The introduced methodologies have been tested on data gathered from a subject. In direct and lengthy comparison, the most successful site for the EMG sensor was the Quadriceps Tendon. It was felt that this was a reasonably realistic position as it could be within the socket of the prosthesis where the stump of the residual limb sits. Figure 1 shows a set of typical signals captured from the sensor at 1 kHz. Three different states have been recorded, as shown. In the standing state a regular signal of approximately ±2v can be seen when the muscle is at rest. Then, as each step is taken, each movement of the muscle causes a sharp increase in amplitude to a peak followed by a slower decrease in amplitude as can be seen in the walking and running states.

A. Feature Extraction

Figure 7 shows a composite of all the results with the absolute signal shown in continuous grey and the spike in continuous black. The features were extracted using both Excel and C++ code. The Excel method was good for rapid modelling and producing quick graphs. However, the C++ method made it much easier to handle values and buffers and provided an output to be directly applied.

In this work, the following four feature selection methods have been studied and compared in detail:

Maximum sample (MAX) - Different values of SS_Max produced different results and with SS_Max set to half the sampling rate the maximum sample generally increases as the state shifts from walking to running, as can be seen in the black dash and dot trace of Figure 7.

Average of samples (AVG) - Experiments were carried out using an average of all the positive signals and of the absolute signals and for some of these values a normalising value, NM_Avg had to be used. Experiments were carried out using different values of SS_Avg. Also the sampling rate was taken into account. Values between 0.5 and 1.5 for the sampling rate were found to be effective. The effect of averaging at 0.5 of the sampling rate is shown in the dotted black trace of Figure 7. As can be seen, the value gradually increases as the samples get closer together and are higher in amplitude.

Cluster Width (CLUSW) - As can be seen in the grey dash and dot trace of Figure 7, the results for this feature are not conclusive. The difference between standing and the other two states is obvious. However, the difference between walking and running is not quite so clear.

Cluster Gap (CLUSG) - The difference between the three states is quite clear for this feature, as shown in the grey dashed trace of Figure 7. As each cluster represents the muscle movement for one step, CLUSG is really a measurement of the gap between steps. A rough experiment on a treadmill showed that while the number of steps per second changes for walking at different speeds, it is almost exactly the same when running

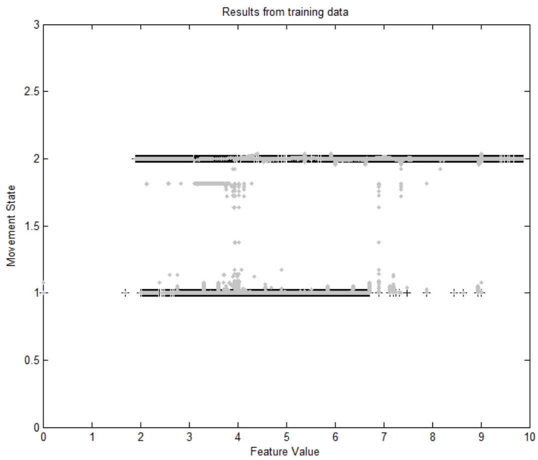

Figure 8 – Training Data. Black dots denote actual data and grey dots denotes ANN outputs.

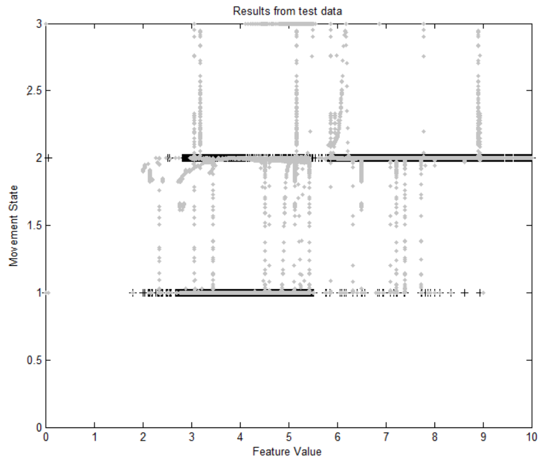

Figure 9 – Test Data. Black dots denote actual data and grey dots denotes ANN outputs.

at different speeds. This is to be expected as most runners extend their stride to speed up rather than increasing the number of steps [20].

B. Accuracy of artificial neural network in state detection

As can be seen in Figure 7, when the four most successful features are captured using optimal feature extraction parameters and placed together, they start to show common tendencies in each of the three states which suggest that they may be suitable for use with an ANN.

Once the different features to be extracted were determined experiments were conducted with different sampling rates. In general, a higher sampling rate tended to give better results and Figure 7 shows the AVG feature at 100Hz (the black trace) and 500 Hz (the grey trace). As can be seen the 100 Hz trace is far more erratic and changing the extraction parameters did not improve this much. However, when the same comparison has been done for CLUSG the time improvement of the higher sampling rate is not as obvious.

The Matlab implemented feedforward backpropagation neural network outlined in Section III.C was trialled first and produced one successful result. It used a two layer network with five input neurons and two output neurons and the four extraction features previously outlined. However, it only managed to distinguish between the walking and running movement states.

Figure 8 shows the results of the training data, which looks very promising. However, Figure 9 shows the results of using a new set of test data on the successful network, which is not as good. It is worth noting that the set of data used to train and the one used to test were taken at different times when the sensor had been removed and repositioned and this difference in signals is an issue that will need to be addressed.

The ranking plots in Figure 10 show the results of the C++ implemented ANNs with different learning and transfer functions. On the left are the results from the training data and on the right the test data. Each dot represents one trialled ANN with the cross representing the mean of the set of tests. From the training data test results it appears that using all four features produces the best mean results followed by AVG, CLUSW and then CLUSG. While the test data results also show all four features to provide the best mean results, here CLUSW performs better than AVG. The best all feature vector ANN, as measured on test data, was able to correctly identify the walking *state 95.8% of the time. The best AVG and CLUSW based ANNs were able to achieve over 96% accuracy. Although it is difficult to directly compare, these results are relatively high compared to other research such as the work by Huang et al [21] where results are reported to range between 70% and 90%.

It is not surprising that the successful ANN consisted of roughly the same number of input and output neurons as there were inputs and outputs. The chosen features mean that the traces for walking and running were quite distinctly different and so extra neurons would not be necessary to choose between the two patterns. What was surprising is that the ANN was not able to distinguish between standing and walking. Further experiments may lead to success in this area but the trace for this movement state was so distinct that better results were expected.

It was also not possible to distinguish between running at two different speeds. This may, in part, be due to the fact that CLUSG does not significantly change at different running speeds.

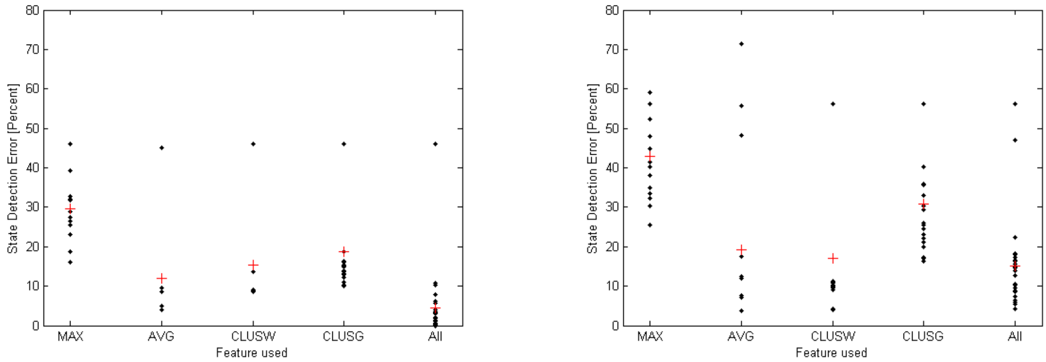

Figure 10 – Comparison results of Training data and Test data when passed through a series of ANNs

V. Conclusions

In this paper we have presented the possibility of using the outputs from an EMG sensor on the surface of the skin of a leg to determine the wearer's movement state. A suitable site was found on the leg for the EMG sensor and signals from the sensor were then recorded. A number of features were extracted from the recorded signals using a variety of extraction feature parameters. These features were then passed through ANNs to train them to distinguish between standing, walking and running states.

The features extracted have yielded successful neural networks which can distinguish between the different walking states. While the best AVG and CLUSW feature vectors based ANNs showed excellent accuracy of over 96%, the best mean performance over all test ANNs was achieved by using all feature vectors.

The success of these experiments shows that the ANN has the ability to learn how to distinguish between different movement states based on the extracted features. In a real life situation the ANN would be trained for each individual wearer and would therefore learn their own walking and running styles. It would then be possible to retrain the ANN as the wearer's ability improved or changed. It is also hoped that it will be able to learn a variety of different other states and the transition between one state and another such as sitting to standing and stair climbing.

The speed with which the trained ANN can then make decisions about the current movement state make it ideal for use in controlling a micro-processor controlled limb in real time. This means that the output from the EMG sensor can provide the required sensory data to control a microprocessor controlled prosthetic limb. This would mean that a wearer of such a prosthetic limb would be able to move around more naturally and change the movement state of the limb without the need for a remote control.

The main aim of this research was to explore techniques to best detect the walking and running states of the user including finding the best locations for placing the EMG sensors and extracting useful features from the captured signals. Further work is planned with larger quantities of data collected on a treadmill and from more volunteers. It is also planned to develop a method of dynamically recording the movement state rather than manually determining it. This may further strengthen the accuracy and reliability of the proposed methods. Eventually these techniques will be tested directly on a completely self-sufficient prosthetic limb.

Acknowledgments

The authors would like to acknowledge the assistance of Thomas Stubington, the trainee doctor who provided assistance in finding the relevant sites for the sensor.

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Multiple sensor outputs and computational intelligence towards estimating state and speed for control of lower limb prostheses

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Abstract—**For as long as people have been able to survive limb threatening injuries prostheses have been created. Modern lower limb prostheses are primarily controlled by adjusting the amount of damping in the knee to bend in a suitable manner for walking and running. Often the choice of walking state or running state has to be controlled manually by pressing a button.**
This paper examines how this control could be improved using sensors attached to the limbs of two volunteers.
The signals from the sensors had features extracted which were passed through a computational intelligence system. The system was used to determine whether the volunteer was walking or running and their movement speed.
Two new features are presented which identify the movement states of standing, walking and running and the movement speed of the volunteer. The results suggest that the control of the prosthetic limb could be improved.

I. Introduction

The development of effective and functional prostheses has become increasingly important as more people survive limb threatening injuries. In [1] we learn that there are 32 million amputees worldwide and that over 75% of major amputations are lower limbs.
While many of the problems facing those trying to produce functionally realistic prostheses are being solved the way in which the units react to changes in the movement state and speed of the wearer still has to be controlled manually.
This paper examines whether this area could be improved by using features extracted from sensors placed on the prosthesis and on the prosthesis wearer's body. Such features include the average sensor output calculated over a sliding window and rate of change of a sensor output over two samples. A computational intelligence (CI) system was used to determine from the features whether the volunteer was walking or running and what speed they were moving at. This work continues the work described in [2].
Recent improvements in all areas, including materials, computer processing times and battery technology, mean that a microprocessor controlled prosthesis is now a reality. However, the challenge has always been to create a system that could be wearable and usable. The following literature review looks at current research in these areas. This paper is divided into seven sections. A literature review is presented in section two, feature extraction is discussed in section three and pattern classification in section four. In section five the experimental setup is outlined. The results are presented in section six and final conclusions are drawn in section seven.

II. Literature Review

In general, there are two ways in which computational intelligence can be used for prostheses control. The first is interpreting signals from the wearer to determine what movement they are making and the second is in controlling the actions of the limb, here there is a large overlap between the development of prostheses and that of robots and exoskeletons.
In all cases the artificial limbs must move and balance like a human limb to be successful. Again, this area of control can be split into two. The first being simple pattern recognition to determine a state for the prosthesis from the incoming signals. The second is in the control of the entire walking gait of a bipedal robot.

A. The use of sensors in prosthetic limb control

Several types of sensor have been used to help with the control of a prosthetic limb. The current state of the art in the use of these sensors is considered in the following subsections.

1) Electromyographic sensors: Figure 1 shows a typical EMG sensor output with examples of the signal recorded during walking and running.
Much research has been done into the fact that the residual limb can still give the signals required to control the missing portion of the limb and in [3] the challenges of doing this are discussed. One of the main challenges is the fact that each step from each individual will produce different signals at different times making pattern recognition very difficult. In [4] the fact that the signals that reach the surface mounted EMG sensor have had to pass through other muscles, tissue and bone, all of which will have an effect upon the signal is discussed.

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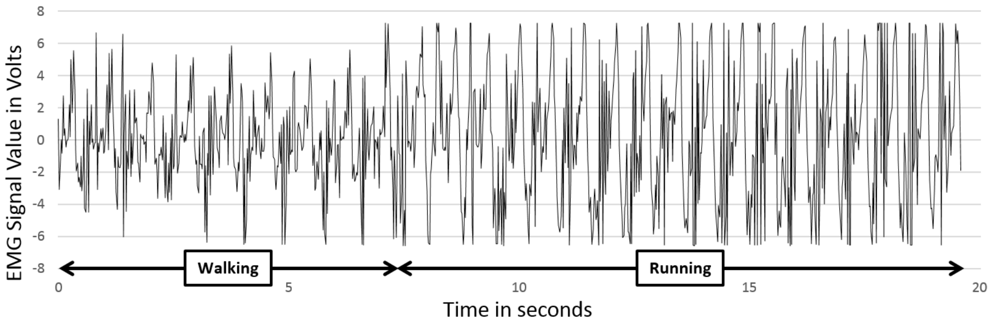

Fig. 1: EMG sensor output taken from a volunteer's thigh while walking and running.

The use of signals from an EMG sensor to control a prosthetic arm were being reported on as early as 1967 [5] to simply open and close a hand. Now the research has developed to the point where EMG signals are being used in real time to control a prosthetic hand [6]. In [3] an EMG sensor is used to distinguish seven movement modes for a lower limb prosthesis including level-ground walking and turning. In this work three movement states are distinguished, standing still, walking and running.

Volitional control of the muscles has been examined by [7] where the quadriceps and hamstring muscle EMG signals were used to directly interpret the users intent to flex or extend the knee.

It is very easy to think only of adapting the prosthetic to fit the person. However, in some circumstances surgery has been performed to transfer nerves to a more accessible position for the EMG sensors. This has then allowed signals to be detected that would otherwise have been impossible to find. This has been used in a number of situations for upper limb prosthesis [3, 8].

It is suggested that this technique could be used for lower limb amputees in the future. In [9] the nerves that used to control the part of the limb that has been amputated were transferred to a spare muscle then surgically re-innervated. This technique allows the signal that would have been sent to the missing part of the limb to be more effectively captured and used to control a prosthetic.

In [10, 11] the authors used EMG signals to directly control an exoskeleton. This has potential for assisting disabled people who are no longer able to walk and for rehabilitating someone with a disability. EMG also has extensive application for analysing the walking gait of non-amputee's [12] and this research could also help in the development of a successful control system.

2) Pressure Sensors: The walking gait of humans has been very thoroughly studied and from [13] we learn that a typical gait cycle for level ground walking consists of two phases: stance and swing. The stance phase begins at heel strike and terminates upon toe off; the swing phase takes up the remainder of the cycle. In [14, 15] and many other papers the usefulness of the pressure sensor for detecting movements within the gait cycle of a prosthetic is examined.

Some studies place the pressure sensor between the residual limb and the socket of the prosthesis. This will give a basic idea of whether or not the prosthetic is currently in a load or non-load bearing state. In [16] the effectiveness of this strategy is compared with the use of EMG sensors in the socket of the prosthesis. Furthermore, some authors have used pressure sensors to determine if the user is sitting or standing.

3) Accelerometers: Accelerometers have been used for a variety of tasks in the evaluation of the movement of limbs. In [17] an accelerometer is used to record and confirm the movement of the user while wearing an EMG sensor. This information is then used to determine any adverse effects the movement of the wearer has on the EMG sensor.

B. *Signal processing*

Once signals have been collected from the various sensors they need to be processed to make them usable by a classification system.

1) Pre-processing: In [18] the signal processing consists of passing the raw signal from the pre-amplifier through a low-pass filter. The signal is then rectified by taking the absolute value and normalised using the maximum muscle contraction measured before experimentation. This technique uses a sliding window to calculate the average of the last n signals in the window.

2) Feature Extraction: The information that comes from the EMG sensor, shown in Figure 1, is in the form of a signal which an ANN would not easily be able to recognise. It is necessary to extract the relevant features that distinguish one state from another. In [19] this is described as the main kernel of classification systems and is essential to the motion command identification.

The authors also highlight that it is difficult for a single

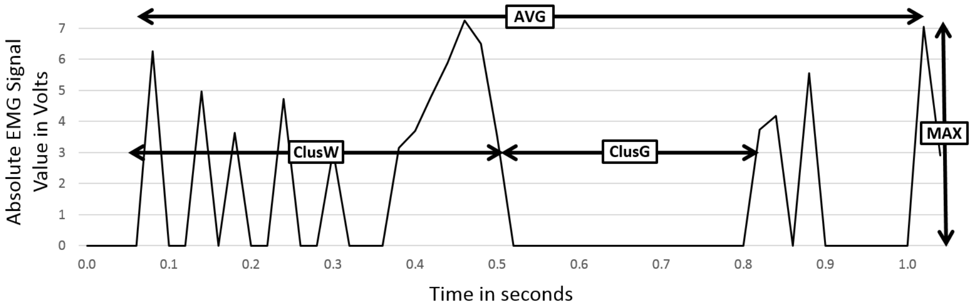

Fig. 2: A visual interpretation of the features extracted from the EMG output.
(Note that the absolute value of the output has been used to allow
the background signal of ± 2.8 volts to be removed by thresholding)
MAX = maximum of last n samples ClusW = width of last cluster of spikes
AVG = average of last n samples ClusG = gap between last two clusters of spikes

feature to reflect the overall state of the signal. Thus, several different features are required.

In [1] four time-domain features were extracted from the EMG signal, the mean absolute value and the number of zero-crossings, the waveform length, and the number of slope sign changes. These were then used for real-time prediction of the intent to sit or stand.

Other techniques used to extract features include filtering [4]. Most papers agree that the extraction of data from this signal in a timely fashion is one of the hardest aspects of the process.

C. Pattern classification

Once the features have been extracted from the EMG signal they need to be used to distinguish between different states. This process involves looking at the patterns within the signal features and then training a classifier to recognise and separate these patterns. Computational Intelligence techniques are often used for this and could include fuzzy mapping functions [19] or different varieties back propagation ANN [4, 20].

D. Controlling a limb or prosthesis

The final part of the process is to control the limb. In [21] the inputs from the EMG are passed through a dynamic recurrent neural network (DRNN) to control all three sections of a virtual limb on a computer based simulation. A real control system is discussed in [22] where the authors have studied the intricacies of walking at length. They use a feed forward neural network to overcome the limitations of rule based control systems which are unable to take account of changing demands and terrain. A simulation of a powered prosthesis was successfully controlled.

The Plymouth Hand [4, 20, 23] project has extensively researched the use of an EMG signal to control a prosthetic hand. The authors describe how a single EMG signal is gathered and passed through a series of filters to remove noise from the mains electricity. The signals where then fed into a neural network which had been trained to recognise a series of positions for the hand to move into.

III. Feature extraction and pattern classification

In the previous work [2], several features were extracted from an EMG sensor output. These features, shown in Figure 2, allowed an artificial neural network to distinguish between walking and running by returning a state of 1 for walking or 2 for running.

In the current work extra sensors were added attached via Arduino boards to record new data. These sensors included:

- A wheel sensor attached to a treadmill to record the speed of the volunteer
- Six pressure sensors, one under the heel, toe and ball of each foot
- Four accelerometers, one on the thigh and calf of each leg

The pressure sensor and accelerometer sensors were mounted on a harness so that the volunteer could safely wear them while walking and running on a treadmill as shown in Figure 5. The data was then collected from the sensors as outlined in the following sections.

A. Wheel sensor

The wheel sensor was attached to the treadmill. The Arduino code for this sensor was set to continuously count the number of times the wheel made a complete revolution. An interrupt was set to trigger every 1/50 of a second and when this interrupt occurred the wheel counter reading was taken and then the counter was zeroed. This gave the number of revolutions made in the last 1/50 of a second and from this the speed of the treadmill and therefore of the volunteer could be

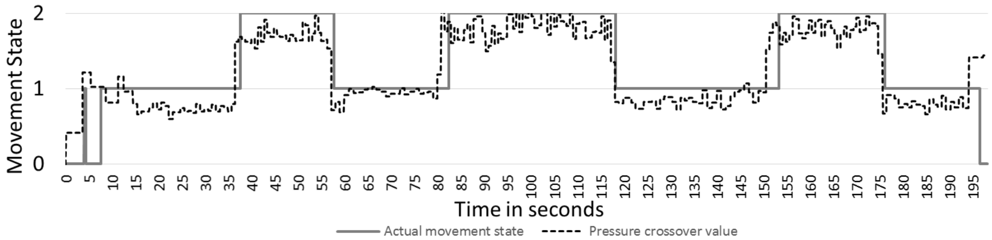

Fig. 3: A comparison of the crossover points of the heel and toe pressures with the actual movement state determined from the wheel speed sensor

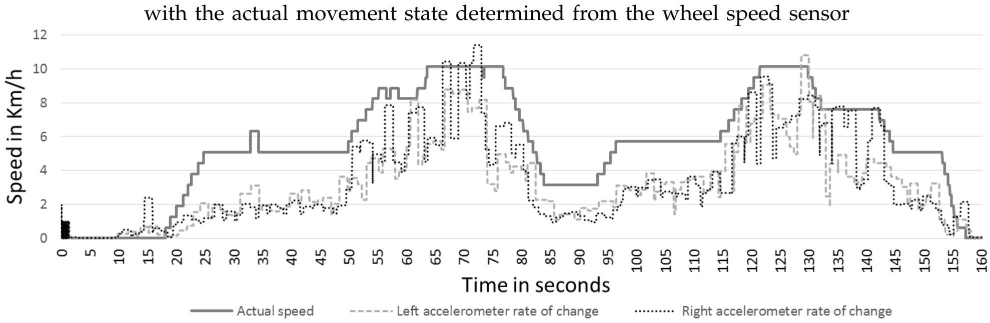

Fig. 4: A comparison of the left and right accelerometer rate of change to the actual speed determined from the wheel speed sensor

calculated in Km/h. As the wheel sensor experienced some interference, the value achieved was averaged over the last n readings and n was varied through experimentation to enhance the results.

B. *EMG sensor*

The features derived from the EMG sensor in the previous work were trialled again as part of this work.

C. *Pressure sensors*

The different parts of the walking and running cycle were analysed. From this analysis and examination of the outputs from the pressure sensors, it was found that there was a close correlation between the relative change in heel and toe pressures and whether the volunteer was standing, walking or running.

Figure 3 shows the results of this feature as a black dotted line with the actual recorded movement states of standing (0), walking (1) and running (2) shown in solid grey. As can be seen, there is a strong correlation. However, there is a certain amount of noise at the changeover points. This is because the current method of determining that the recorded movement has gone from walking to running is to threshold it at a given speed and this is clearly open to interpretation. Not only is it possible to walk and run at the same speeds but there is a changeover step where the movement state is half running and half walking as the changeover occurs. This applies when both accelerating and decelerating. It is also possible that this changeover step is being exaggerated by the delay as the treadmill changes speed.

D. *Accelerometers*

From examination of the accelerometer readings and experimentation a feature was found that was able to approximately estimate the speed at which the volunteer was moving. This feature was found by taking the current accelerometer reading from the previous one to give a rate of change and then averaging this reading over the last n readings, where n was varied through experimentation to enhance the result.

Figure 4 shows the values for this feature for both the left and right accelerometer compared with the speed measured by the wheel sensor (the speed has been normalised for comparison purposes). The two dotted lines show the left and right accelerometer rates of change and as can be seen the general shape of the change correlates well to the measured speed shown in grey.

E. *Artificial neural networks*

The new features discovered from the new sensors and the successful features from the previous work were then passed through a series of artificial neural networks for pattern classification. Two different artificial neural network implementations were trialled. The first was the original Multi-Layer Perceptron (MLP) from the Matlab

Set No.	Features used as inputs to the ANN				
Set 1	ClusG	ClusW	AVG	MAX	
Set 2	ClusG	ClusW	AVG	MAX	PRESS
Set 3	ClusG	AVG	PRESS	ACCL	ACCR

TABLE I: The three sets of features trialled as the inputs to the ANN
Set 1 - original feature set from previous work
Set 2 - original features and new pressure feature
Set 3 - two original features and three new features

artificial neural network toolbox used in the previous work using a tansig transfer function. The second was implemented using the Netlab toolbox [24] which allows a vector of options to tune parameters such as the response function and the gradient optimisation. This was also an MLP with linear output node response and a scaled conjugate gradient (scg) optimisation method. Other response functions and optimisation methods were trialled without success.

Each artificial neural network configuration was trialled with a number of training and testing data sets and the results were compared. As part of the trials, different sets of features were chosen. As can be seen in Table I three feature sets were used. It was found that feature sets 2 and 3 were the most successful and these were taken forward to the main testing.

Fig. 5: A volunteer wearing the sensor harness.

IV. Experimental Setup

The new sensors were combined with the EMG sensor using Matlab code to collect and process the data.

A. Volunteers

Data was captured from two volunteers.

- **Volunteer one** is a 48 year old female with no amputation and is shown in Figure 5.
- **Volunteer two** is a 30 year old male with one prosthetic leg. At the time of the experiments volunteer two was unable to run on a treadmill and so only walking data could be captured for him.

B. Sensors

Three Arduino boards were used to interface between the new sensors and the computer, the following sections explain the use of each sensor.

1) Wheel sensor: The wheel sensor was attached to a small, dedicated Arduino board and consisted of a small rubber wheel attached to a rotary encoder which registered a tick each time the wheel completed one rotation. Code was written to send an interrupt to the Arduino board every 1/50 of a second. The ticks were counted until the interrupt occurred at which point the counter was zeroed and the number of ticks were transmitted over a serial connection.

2) Electromyographic Sensor: An EMG sensor was used to pick up the signals sent by the nerves through the leg to control the muscles. The EMG sensor used for this research consists of:

- Motion Lab Systems MA 317 A300 A3 Preamplifier
- Amplifier circuit to further increase signal levels
- Data Translation DT9801 Multifunction USB Data Acquisition Module
- Data Translation QuickDAQ 2014 software

In order to get a strong, accurate output, the placement of the EMG sensor on the volunteer is crucial and needs to be tested before experiments are run. On volunteer two it was found that placing the sensor in the top of the socket was very effective and after positioning the sensor to achieve a good signal, the socket held the sensor in place perfectly throughout the tests.

3) Pressure Sensors: The pressure sensors were attached to the base of the insoles of a pair of trainers. The three sensors were positioned so that they would be under the toe, ball and heel of the foot.

4) Accelerometers: Four accelerometers were used for the experiments these were placed on the left and right thigh and calf. Each accelerometer returned three values giving the amount of movement in the x, y and z planes.

C. Using the sensors with a treadmill

The wheel sensor was positioned in such a way that the wheel was held against the treadmill gently but firmly. The two Arduino boards and the Data Translation unit for the EMG sensor were mounted in a wearable tool belt as shown in Figure 5.

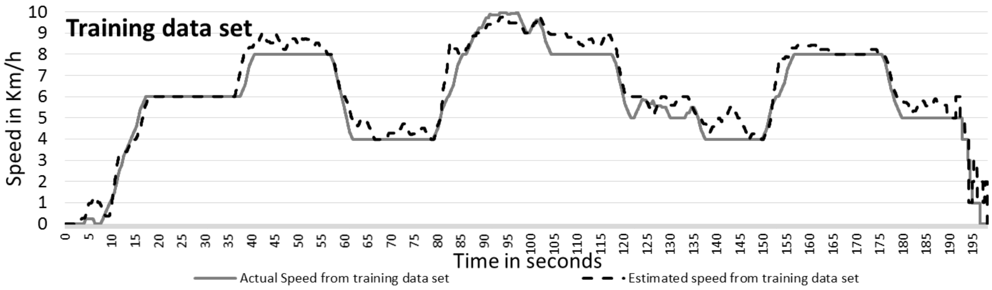

Fig. 6: Example of successful estimation of speed from the training data set. The actual recorded speed is shown in solid grey and the speed estimated from the features by the artificial neural network in dotted black.

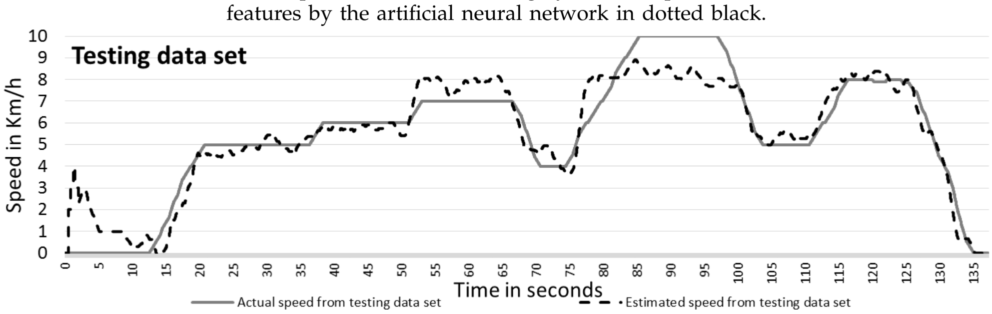

Fig. 7: Example of successful estimation of speed from the testing data set. The actual recorded speed is shown in solid grey and the speed estimated from the features by the artificial neural network in dotted black.

Error type	Feature Set	MSE	RMSE
Best - speed	3	1.132	1.064
Worst - speed	2	12.398	3.521
Best - state	3	0.057	0.239
Worst - state	2	0.392	0.626

TABLE II: The relative error values from the best and worst runs of the test data for speed and state estimation

D. *Data collection*

Code was written for each Arduino board which implemented a timer interrupt every 1/50 of a second. Each time the interrupt occurred the values of the relevant pins on the Arduino board were written over the serial connection and ExtraPutty was used to capture this. Using this method, four good data sets were acquired.

V. Results

The object of this work was to use the features extracted from the new sensors to identify the movement state and movement speed of a volunteer.

A. *A meaningful error value*

Trials were carried out using the data sets as both the train and test input in every possible combination. Two outputs were tested, movement state and actual speed. To compare the results the calculated errors from each run of the artificial neural networks were exported to a file along with the relevant settings used for that run and then compared. It was found that no single data set produced better results. This showed that the results were independent of the data set. It was also found that there were no noticeable differences between the results for the different artificial neural network configurations (ie topology and learning parameters).

The best and worst errors found when estimating the actual speed and when estimating the movement state from the test data is shown in Table II. In each case the feature set that was used is shown. As can be seen, feature set 3 produced the best results showing that the new features gave the best estimation.

The MSE and RMSE values shown in this table do not appear promising. However, this form of classification does not require a perfect output. For both movement state and actual speed estimation it is sufficient to be close enough to the required output that rounding will correct the value as will be shown in the next section.

1) Lowest error when estimating speed: Figures 6 and 7 show the results with the lowest error for the training run and testing run respectively when estimating the

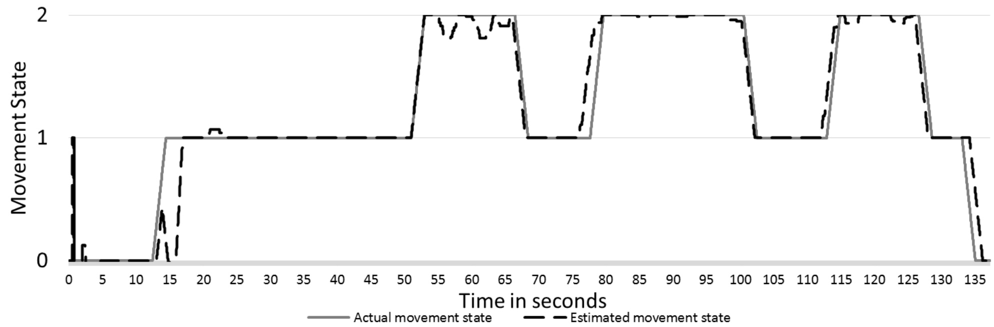

Fig. 8: Example of successful estimation of movement state showing the actual recorded movement state in solid grey and the movement state estimated from the features by the artificial neural network in dotted black

volunteer's speed. While very few samples are exactly correct for the testing run, the black dotted line clearly shows that the system has made a good estimation of the actual speed of the volunteer at nearly every point. Of particular note is the fact that the transitions from one speed to another caused the most uncertainty. This is not unexpected as this is a difficult situation to classify.

It is also interesting to note that the speed of 10 Km/h has not been estimated well and this may be because less than 2% of the training was taken at this speed. It is felt that this result would give enough accuracy to help control the prosthetic.

2) Lowest error when estimating movement state: Figure 8 shows the results with the lowest error for the test run when the volunteer's movement state was being estimated where a movement state of 0 represents standing still, 1 represents walking and 2 represents running.

The results have been rounded and averaged and, as can be seen, closely follow the actual movement state. Less than 5% of the samples are incorrect and the majority of the incorrect samples are around the transition points.

As has been previously discussed, this point is open to interpretation as it is possible to walk and run at the same speeds but there is a changeover step where the movement state is half running and half walking as the changeover occurs and this may be exaggerated by the use of the treadmill.

B. *Processing time*

The code currently takes approximately 10 seconds to process 10,000 samples recorded at 50 samples a second. This suggests a processing speed of 50 ms per sample. Classification of the same sample set takes approximately 10 ms. These figures both suggest that real time processing would be possible.

VI. Conclusions

In previous work the authors have shown that it was possible to distinguish walking from running using a single EMG signal with an accuracy of over 96%. The new work has incorporated further sensors which have provided two novel and effective features from the outputs of the pressure and accelerometer sensors. While the results are still around 96% accurate, they now allow the extra state of standing to be identified. They also allow the system to identify the speed at which the volunteer is moving.

It was only possible to achieve a rough approximation of the state and speed of the volunteer using the new features in their raw state. However, after the use of ANN based models both the state and speed could be estimated well. Two Multi-Layer Perceptron based artificial neural networks were trialled. The first implementation used a tansig transfer function. The second used the linear output node response and a scaled conjugate gradient (scg) optimisation method. In 60% of the tests the second implementation produced a lower error.

The data sets used to create the new features were captured from a volunteer without an amputation. However, data captured from the prosthetic foot and residual limb of a single leg amputee shows identical behaviour. This means that it will be possible to extract the same features from a person using a prosthesis.

As the sensors will be easy to mount and the new features are simple to extract it is likely that this system will work well in real time and thus should support the near real control that will be the focus of further study.

VII. Future Work

This work will be developed by working with the data in real time and moving from the treadmill to real running. Further experiments will be carried out using more precise movement criteria so that the changeover points and uncertain areas can be further tested.

Acknowledgment

The authors would like to thank Ray Foster who volunteered to be tested and Alan McDougall, Senior

Prosthetist at Chas A Blatchford and Sons Ltd.

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Appendix B

Ethical Approval

For official use

Tracking No:	
Date approved:	
Initials:	

Faculty of Technology Application to Gain Ethical Approval for Research Degree Activities

All Research Degree Projects require ethical approval. Research Students in the Faculty of Technology should complete this form to gain Internal Human Research Ethical Approval in consultation with their supervisors and submit it to the Faculty Assessor with their 'Application to Register for a Research Degree form (RDC:R).

NOTE: If your research involves using human tissue or fluid samples or animals please DO NOT use this application form. You should seek guidance from the Chair of the Faculty Human Research Ethics Committee before starting the project.

1. Applicant

Last Name: Hardaker | First Name: Pamela

DMU Email Address: p09272615@myemail.dmu.ac.uk

If you answer any of the following questions with 'Yes', then specific ethical issues WILL be raised that MUST be addressed. You will need to explain in detail in section 3 how you will address these ethical issues.

Has your research proposal identified any of the following research procedures?

Gathering information from or/and about human beings through: Interviewing, Surveying, Questionnaires, Observation of human behaviour	**Yes / ~~No~~**
Using archived data in which individuals are identifiable	**~~Yes~~ / No**
Researching into illegal activities, activities at the margins of the law	**~~Yes~~ / No**
Researching into activities that have a risk of personal injury	**Yes / ~~No~~**
Supporting innovation that might impact on human behaviour e.g. Behavioural Studies	**~~Yes~~ / No**

Are there other additional factors that could/will give rise to ethical concerns e.g. communication difficulties?

None

2. Ethical Issues identified (State explicitly if no ethical issues are identified)

This research will involve the following activities:

- Capturing signals from a volunteer's legs using a variety of sensors including:
  - Electromyographic sensors attached to the skin of the volunteer.
  - Pressure sensors placed in the shoes of the volunteer.
  - Accelerometers attached to the skin or clothing of the volunteer.
  - Goniometers attached to the skin or clothing of the volunteer.
  - Other sensors as may be needed that may need to be attached to the skin or clothing of the volunteer
- Photographing the volunteer's legs while wearing the sensors to record the location accurately.
- Asking the volunteers to participate in a survey to gather non sensitive information including:
  - Age Height Weight
  - Time since amputation
  - Length of remaining thigh
  - Length of time using prosthetic
  - Type of prosthetic used
  - Method of muscle finishing if known
  - Activities normally carried out
  - Issues with existing prosthesis
  - Desired extra functionality
- The signal information will be used to identify the movement states of the wearer.
- The state identification will then be used towards the control of prosthetic lower limbs.

The following ethical issues have been identified:

- Close personal contact may be necessary to attach the sensors
- There is a small possibility of personal injury

3. How these issues will be addressed:

- Every volunteer will be provided with a full information sheet before agreeing to participate in the experiment.
- Every volunteer will be given the opportunity to ask any questions they have before agreeing to participate in the experiment.
- Every volunteer will be asked to sign an informed consent agreement before agreeing to participate in the experiment.
- The volunteer will be free to withdraw from the experiment at any time throughout the process without giving a reason.
- The volunteer and will not be asked to carry out any activity they would not normally carry out.
- The sensors will only be attached with the full permission of the volunteer and, where possible, they will attach the sensors themselves.
- All information will be stored anonymously in a password protected spreadsheet.

Note: You should consider the following:

- *Providing participants with full details of the objectives of the research*
- *Providing information appropriate for those whose first language is not English*
- *Voluntary participation with informed consent*
- *Written description of involvement`*
- *Freedom to withdraw*
- *Keeping appropriate records*
- *Signed acknowledgement and understanding by participants*
- *Relevant codes of conduct/guidelines*

4. To which ethical codes of conduct have you referred?

BCS Code of Conduct
IEEE Code of Ethics
Technology (Computing Sciences and Engineering) Faculty Human Research Ethics Committee Terms of Reference
DMU Technology Ethics Procedures
DMU Technology Human Research Ethics guidance

http://www.dmu.ac.uk/research/ethics-and-governance/pg-and-research/human-research-ethics/technology/human-research-ethics.aspx

Note: For the Faculty of Technology, these codes typically include those published by the BCS, ACM, IEEE or other applicable codes such as the code of the Social Research Association or specific funding bodies, such as the ESRC. Links to some of these codes are available on the Faculty of Technology FHREC website. http://www.dmu.ac.uk/research/ethics-and-governance/regulatory-codes-and-legislation.aspx

List of accompanying documentation that MUST be submitted to support the application:

- A copy of the research proposal (Application for Registration (RDC:R) form)
- Details of the arrangements for participation in the research by human subjects (including how participants will be recruited, confidentiality procedures, copies of consent forms, any questionnaires that will be used and other documentation as appropriate)
- A copy of all the documentation provided to the volunteer to ensure the clarity of information provided
- Copies of appropriate other ethical committee permissions (internal or external) or supporting documentation
- Other documentation as advised necessary by Supervisory team

AUTHORISATION:

Signature by Applicant

Signed ______________________ Date 16 March 2015

Signature by First Supervisor

Signed ______________________ Date 16th March 2015

Name of Supervisor Benjamin Passow

Conditional Approval - Authorising Signature (FHREC Chair)

Signed ______________________ Date ______________________

Tick here if approval is conditional ☐

<u>Note to applicant</u>: If you receive conditional approval, you may proceed with preparing the project but you must NOT start data collection unless you have met the conditions and received full approval.

Conditions:

Full Approval - Authorising Signature (FHREC Chair)

Signed ______________________ Date ______________________

NOTES FOR GUIDANCE:

1 Respondents' co-operation in a research project is entirely voluntary at all stages. They must not be misled when being asked for co-operation.

2 Respondents' anonymity must be strictly preserved. If the Respondent on request from the Researcher has given permission for data to be passed on in a form which allows that Respondent to be identified personally:

(a) the Respondent must first have been told to whom the information would be supplied and the purpose for which it will be used, and also
(b) the Researcher must ensure that the information will not be used for any non-research purpose and that the recipient of the information has agreed to conform to the requirements of any relevant Code of Practice.

3 The Researcher must take all reasonable precautions to ensure that Respondents are in no way directly harmed or adversely affected as a result of their participation in a research project.

4 The Researcher must take special care when interviewing children and young people. The Faculty REC will give advice on gaining consent for studies involving children or young people.

5 Respondents must be told (normally at the beginning of the interview) if observation techniques or recording equipment are used, except where these are used in a public place. If a respondent so wishes, the record or relevant section of it must be destroyed or deleted. Respondents' anonymity must not be infringed by the use of such methods.

6 Respondents must be enabled to check without difficulty the identity and bona fides of the Researcher.

Anne Smith

From: Ethics - Technology
Sent: 06 July 2015 16:11
To: 'pamela.hardaker@gmail.com'
Cc: 'Ben Passow'; David Elizondo; Research Students; Ethics - Technology
Subject: RE: 1415/267 RE: Ethics registration - Student P09272615

Follow Up Flag: Follow up
Flag Status: Completed

Dear Pamela

Research Ethics Application Approval: 1415/267 *Using multiple sensor outputs and computational intelligence to predict intention for control of lower limb prostheses*

Your application to gain ethical approval for research degree activities has been considered and APPROVED by the Faculty Human Research Ethics Committee (FHREC) on 18 June 2015.

Please be aware that changes to the project plan or unforeseen circumstances may raise ethical issues. If this is the case it is the researcher's duty to repeat the ethics approval process.

Kind regards

Anne

Anne Smith
Research & Innovation Coordinator
Research & Innovation Office (4.64)
Faculty of Technology

DE MONTFORT UNIVERSITY
Gateway Building
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Leicester LE1 9BH
UK
T: +44 (0) 116 250 6519
E: amsmith@dmu.ac.uk
W: dmu.ac.uk

If you're planning to visit De Montfort University, please consider using a greener means of transport. See www.dmu.ac.uk/transport

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From: Bernd Stahl
Sent: 16 March 2015 12:03
To: 'pamela.hardaker@gmail.com'; Anne Smith
Cc: 'Ben Passow'; David Elizondo
Subject: 1415/267 RE: Ethics registration - Student P09272615

Hi all,
I approve by Chair's Action. This will need to go to the FHREC, but Pam is free to start the data collection now.

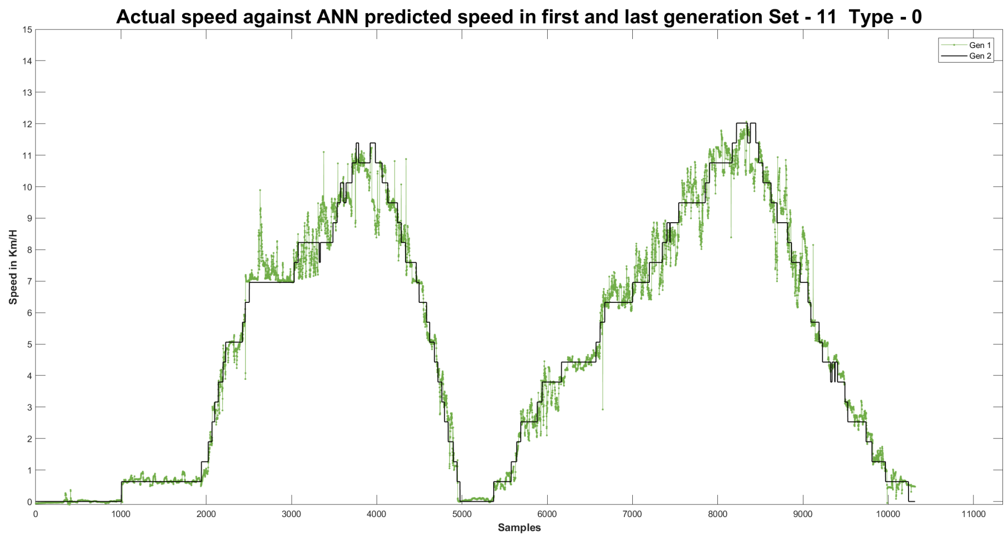
Bernd

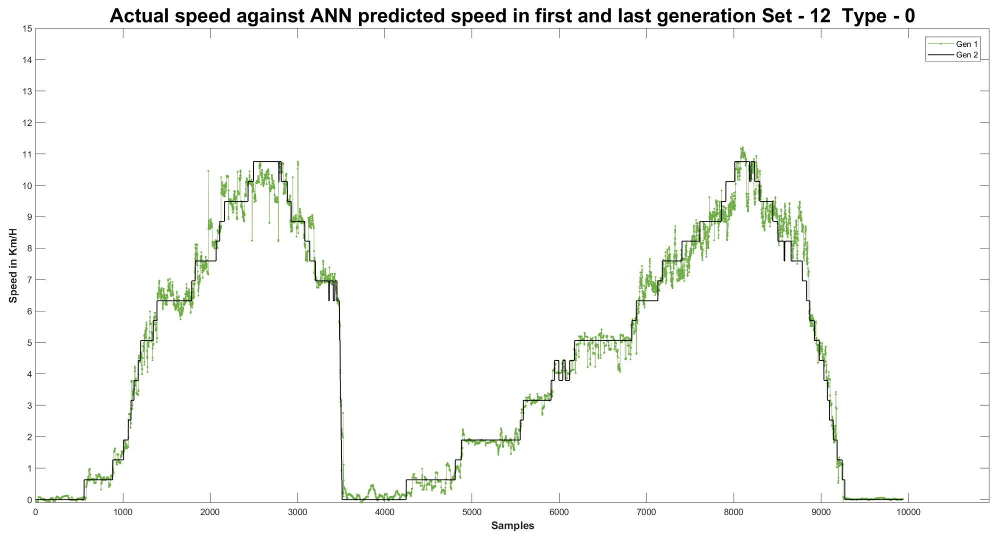
From: pamela.hardaker@gmail.com [mailto:pamela.hardaker@gmail.com]
Sent: 16 March 2015 11:04

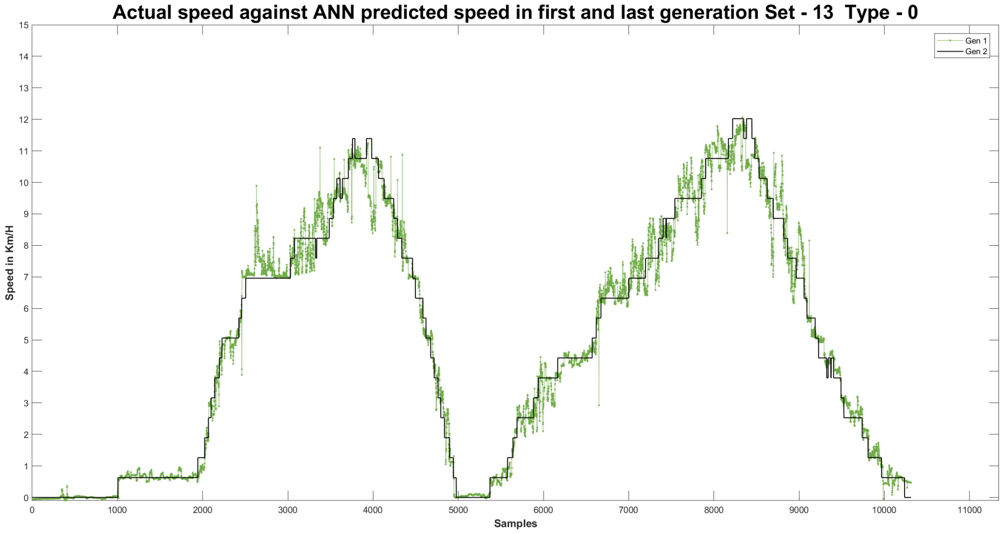
Appendix C

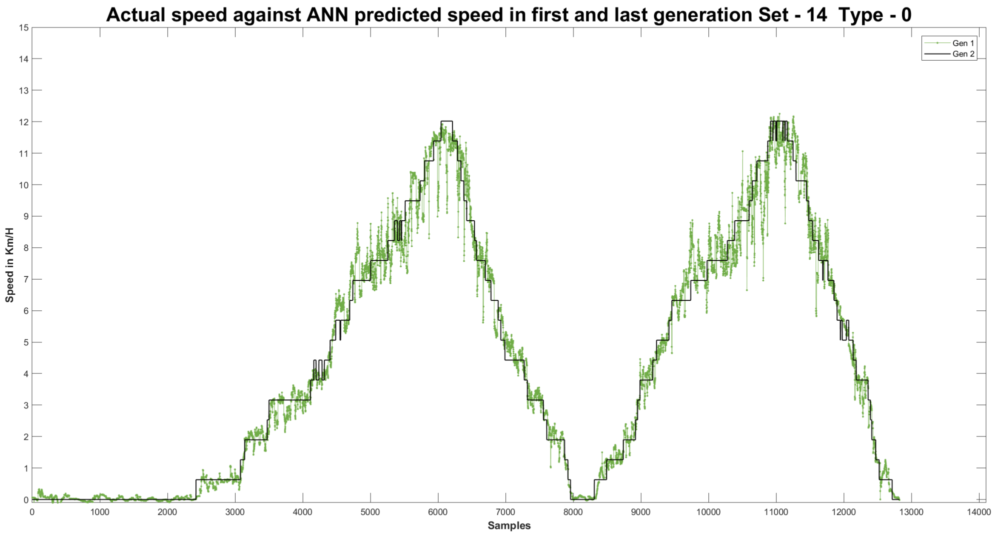
Speed Estimation Results

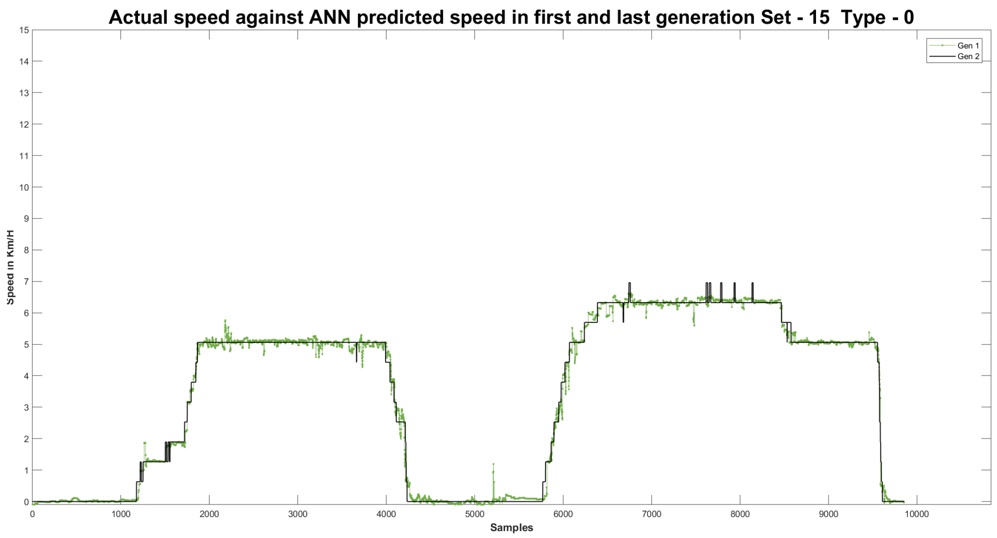
The following diagrams show the actual speed plotted against the speed predicted by the ANN with the lowest MSE for each run.



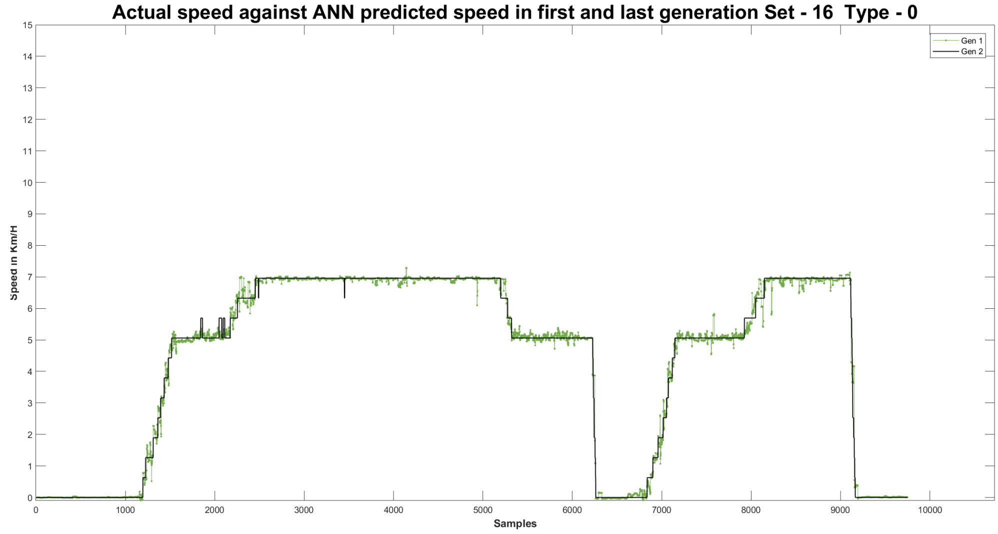



Actual speed against ANN predicted speed in first and last generation Set - 13 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples

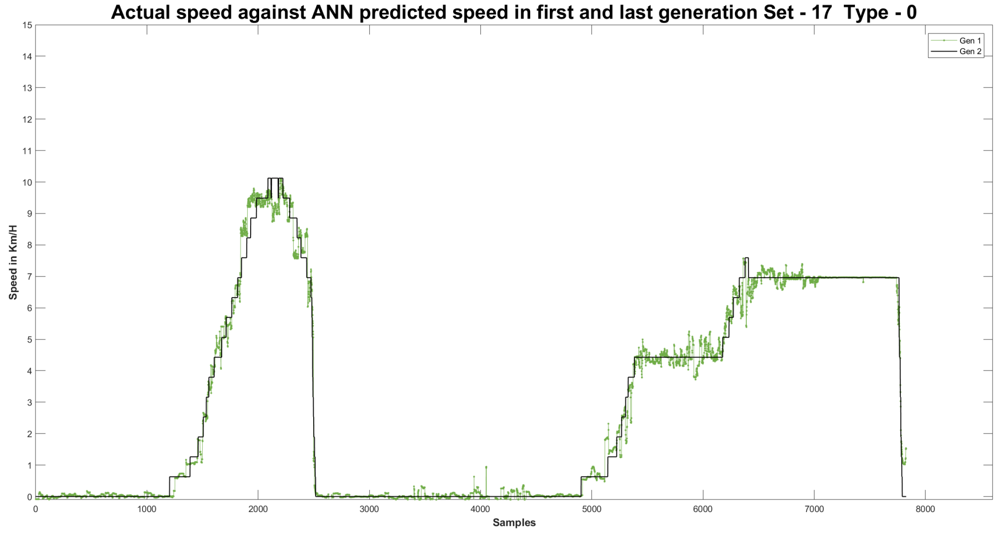

Actual speed against ANN predicted speed in first and last generation Set - 14 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples


Actual speed against ANN predicted speed in first and last generation Set - 15 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples

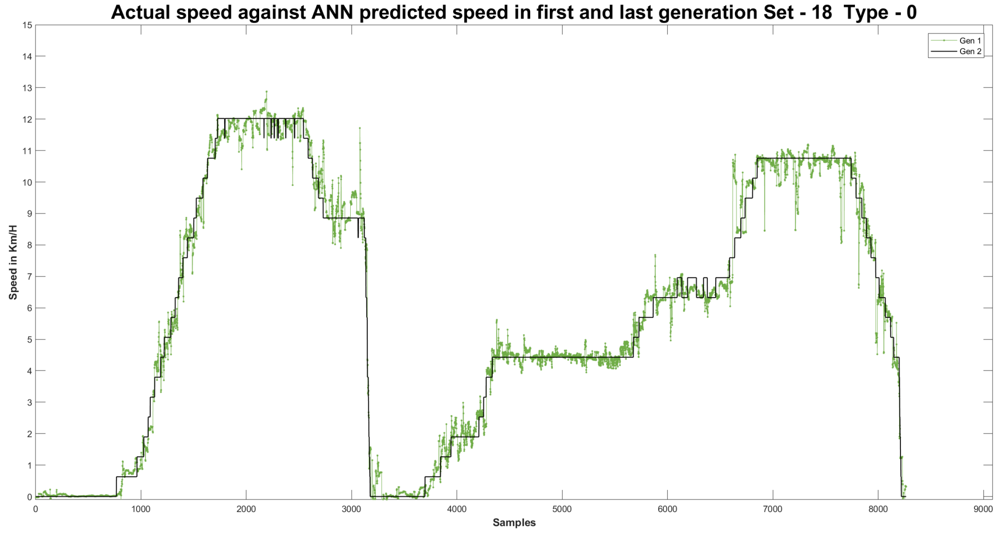
Actual speed against ANN predicted speed in first and last generation Set - 16 Type - 0



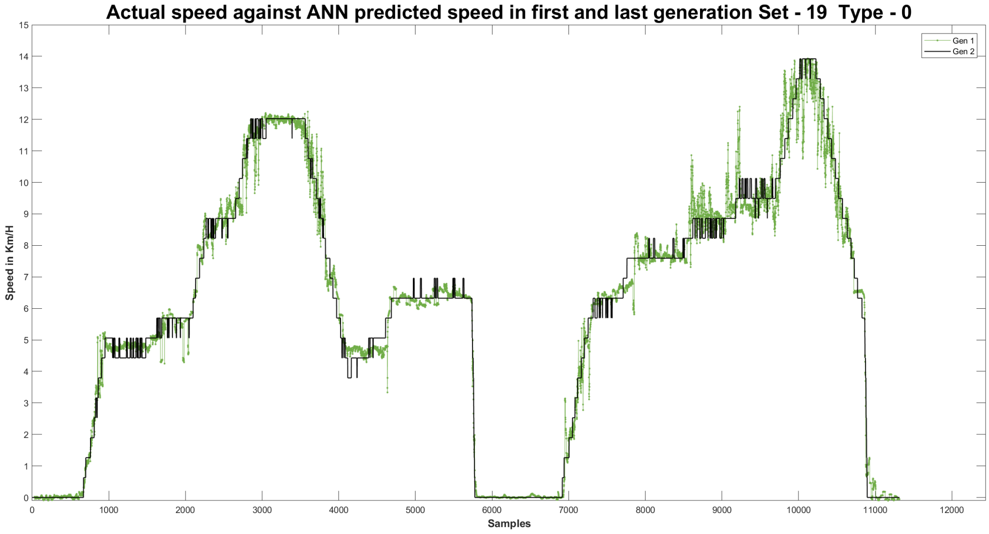
Actual speed against ANN predicted speed in first and last generation Set - 17 Type - 0



Actual speed against ANN predicted speed in first and last generation Set - 18 Type - 0



Actual speed against ANN predicted speed in first and last generation Set - 19 Type - 0



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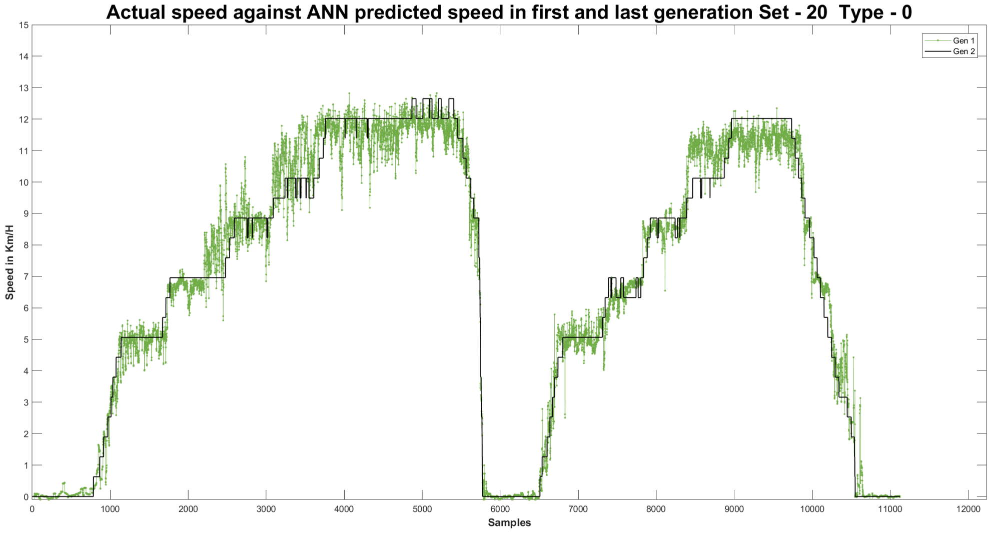

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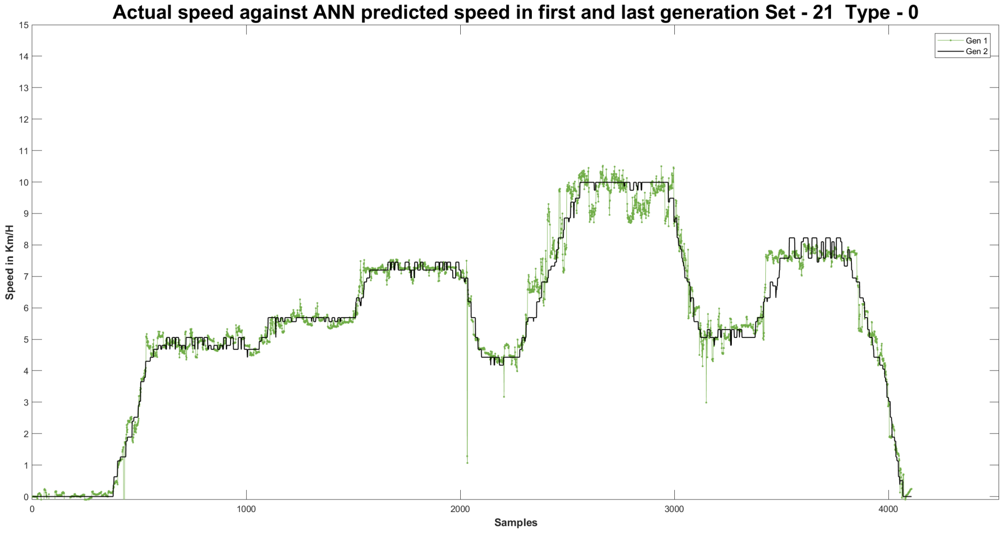
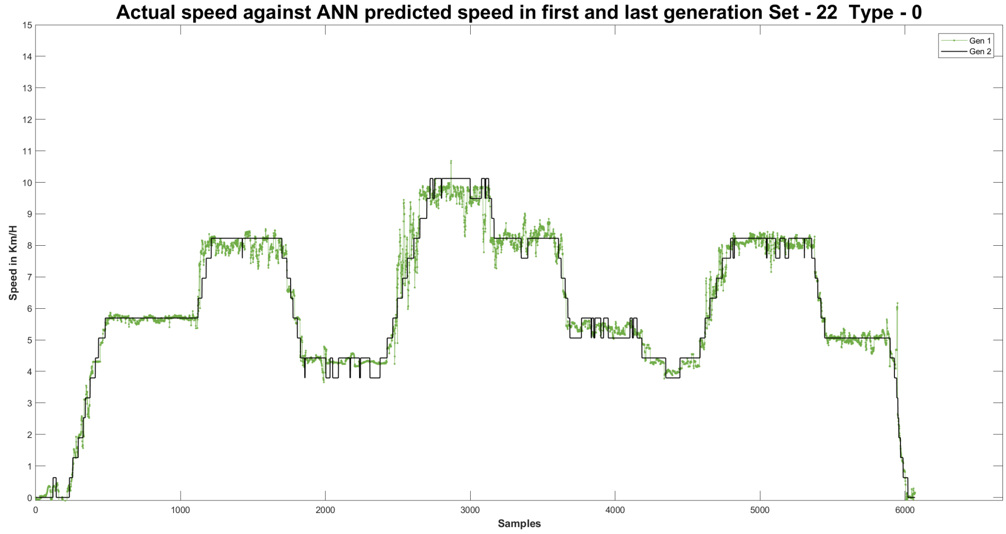
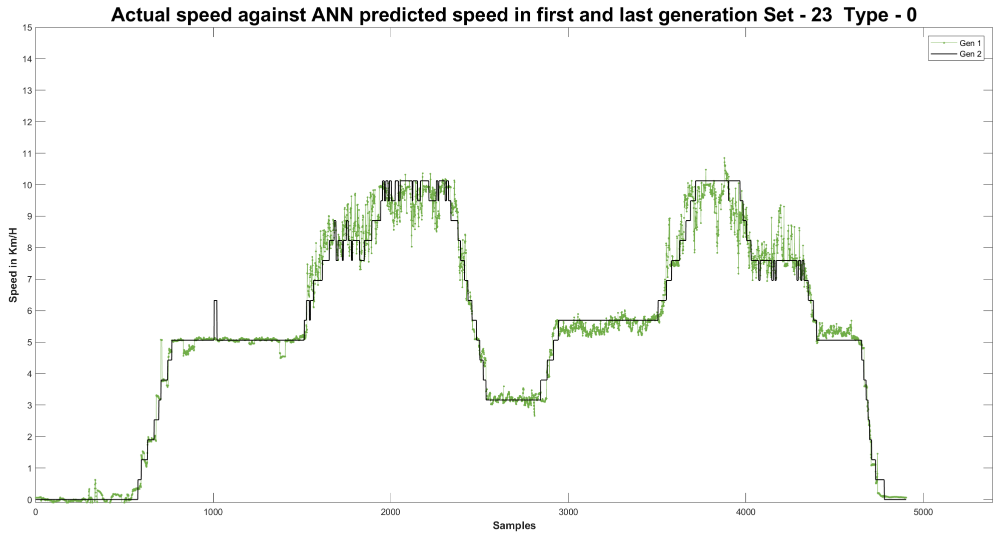
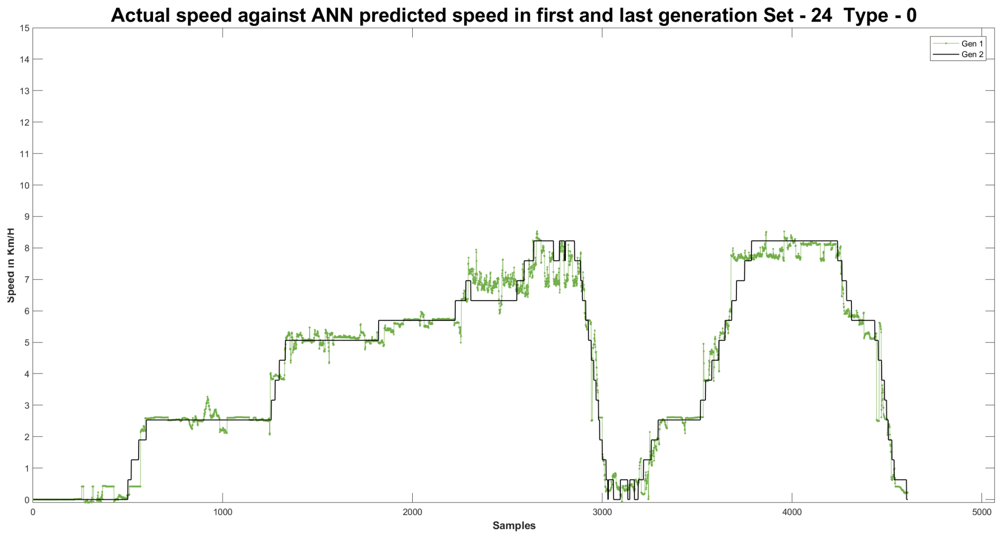
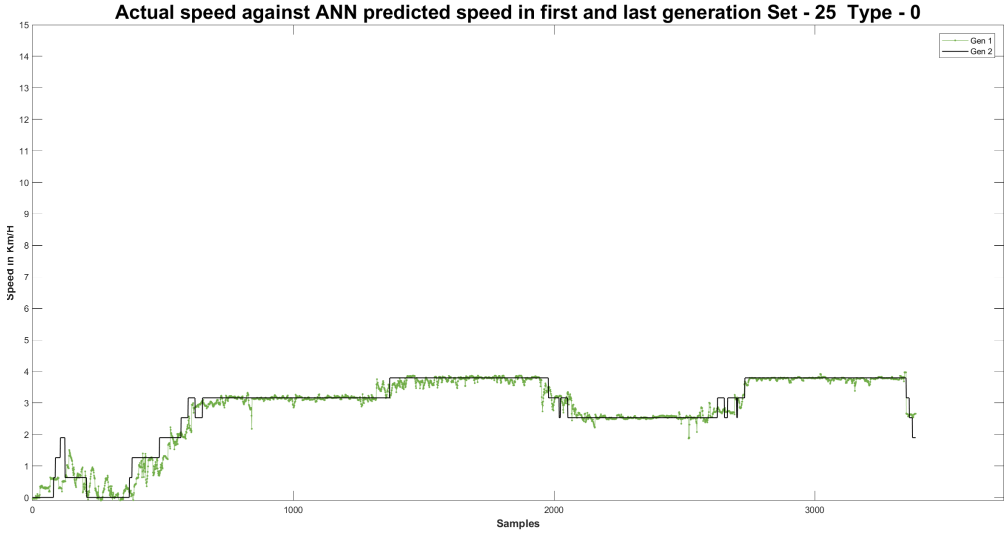



Actual speed against ANN predicted speed in first and last generation Set - 22 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples


Actual speed against ANN predicted speed in first and last generation Set - 23 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples


Actual speed against ANN predicted speed in first and last generation Set - 24 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples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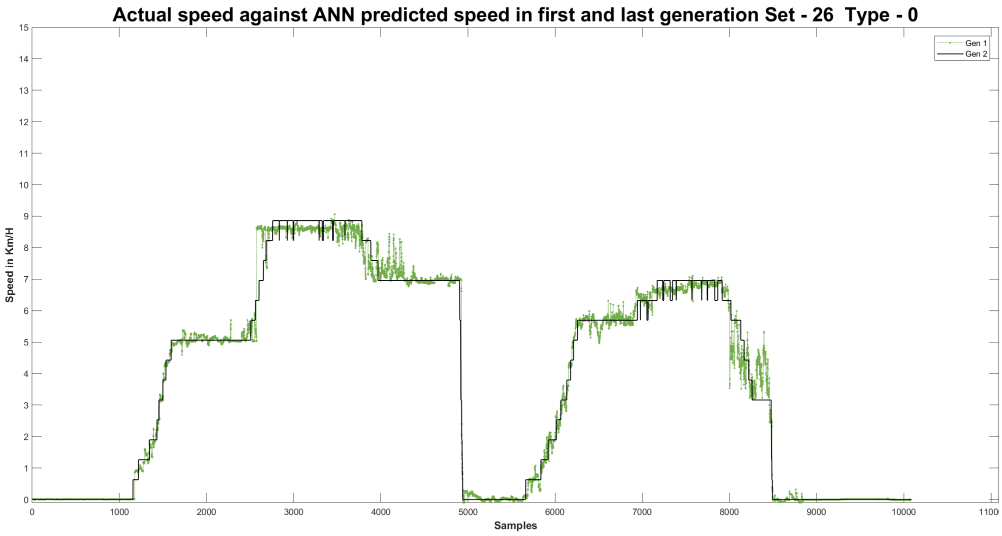
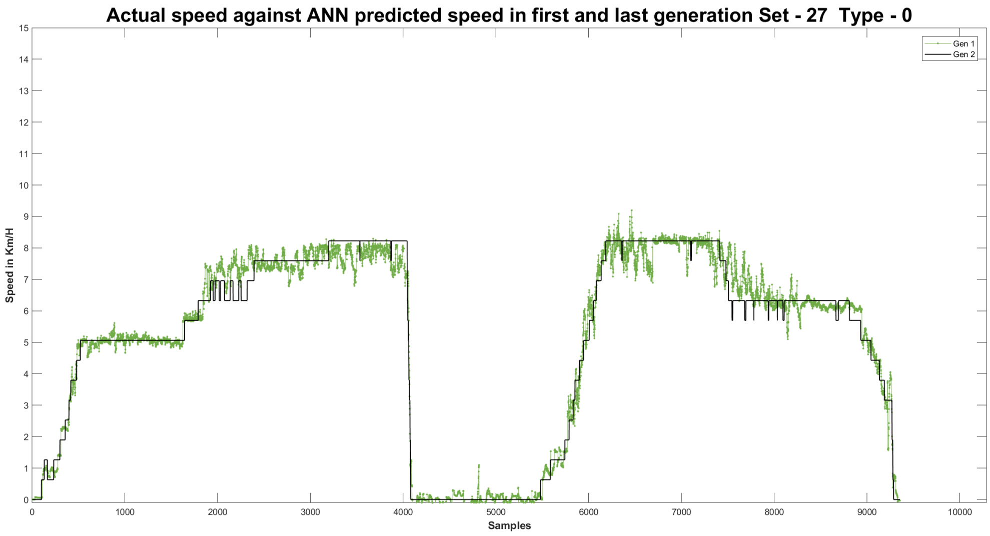
Gen 1
Gen 2
Speed in Km/H
Samples


Actual speed against ANN predicted speed in first and last generation Set - 26 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples

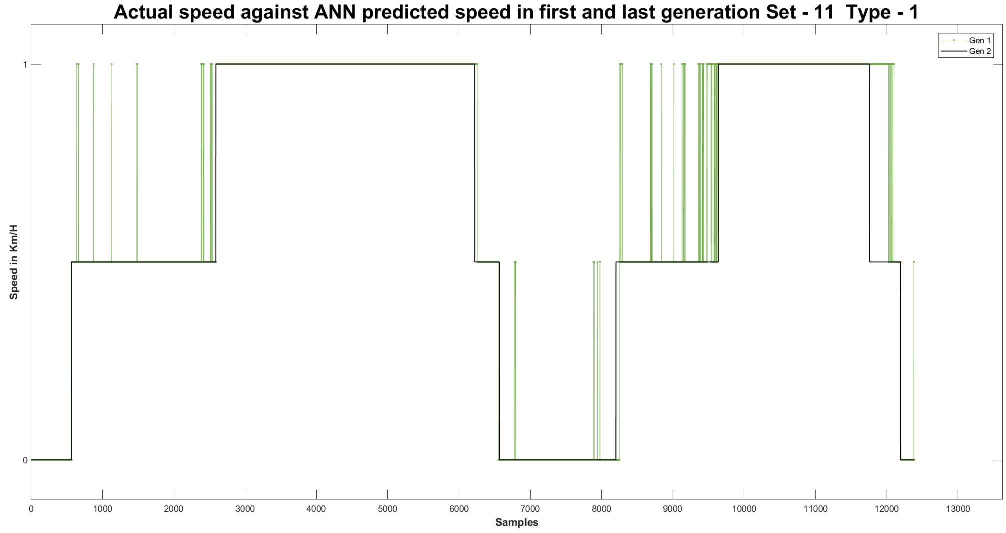

Actual speed against ANN predicted speed in first and last generation Set - 27 Type - 0
Gen 1
Gen 2
Speed in Km/H
Samples

Appendix D

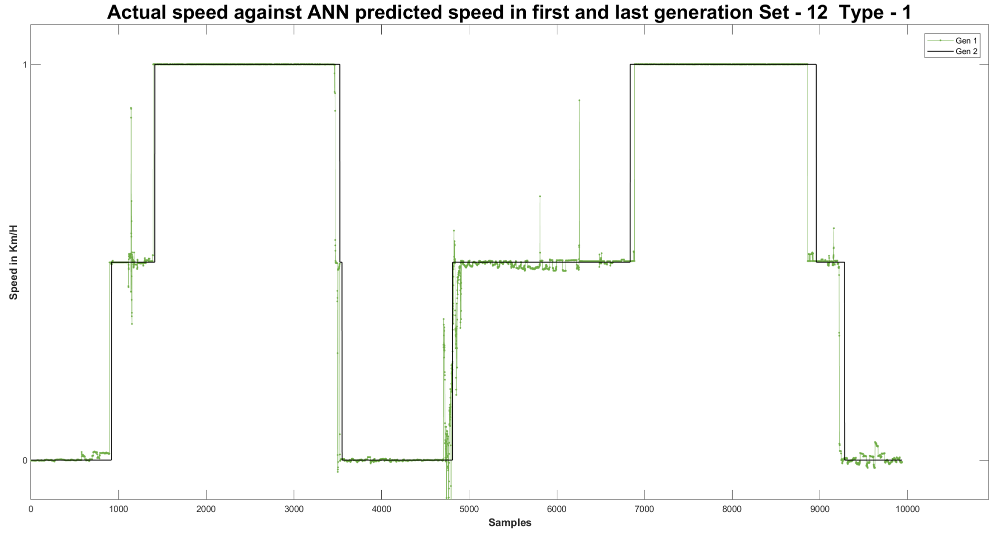
Movement State Results

The following diagrams show the actual movement state plotted against the movement state predicted by the ANN with the lowest MSE for each run.

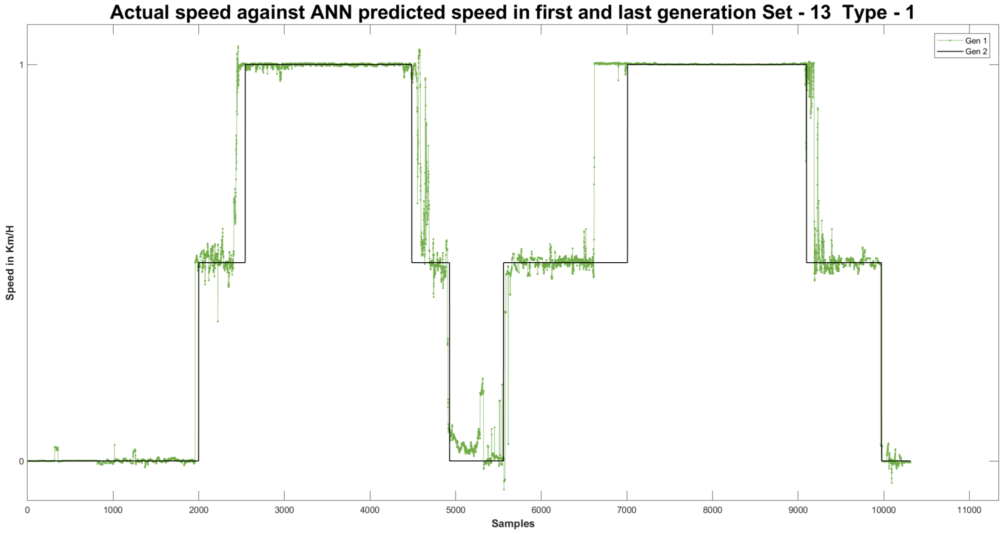
Actual speed against ANN predicted speed in first and last generation Set - 11 Type - 1



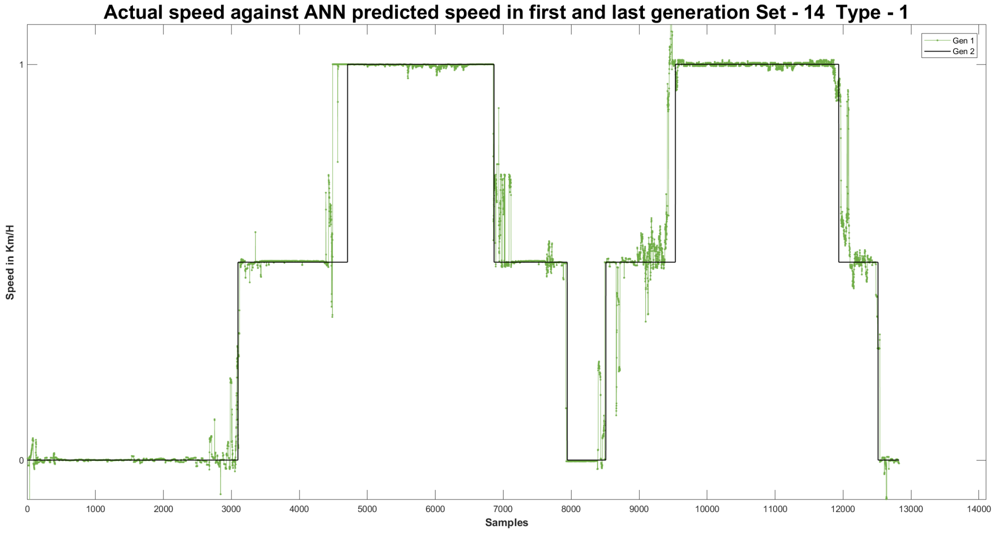
Actual speed against ANN predicted speed in first and last generation Set - 12 Type - 1



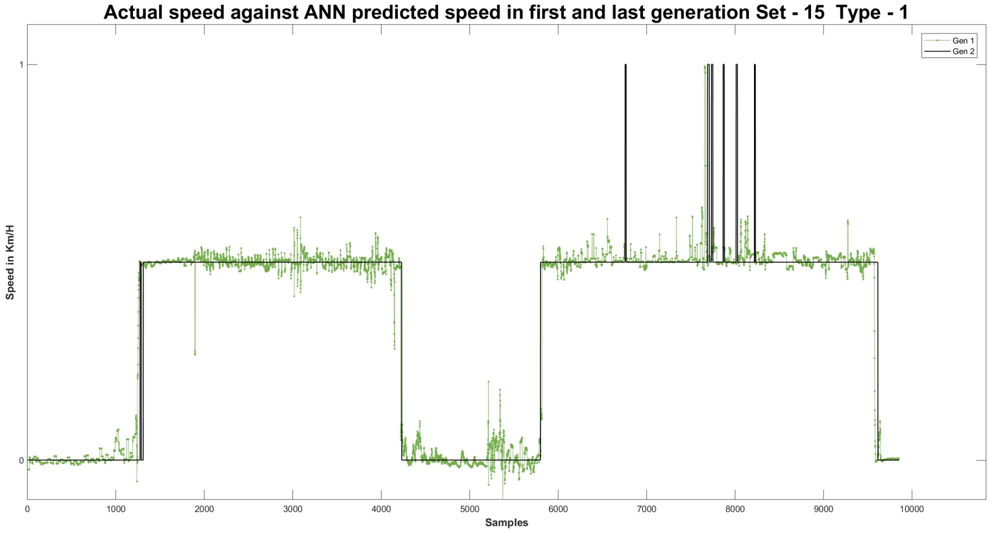
Actual speed against ANN predicted speed in first and last generation Set - 13 Type - 1



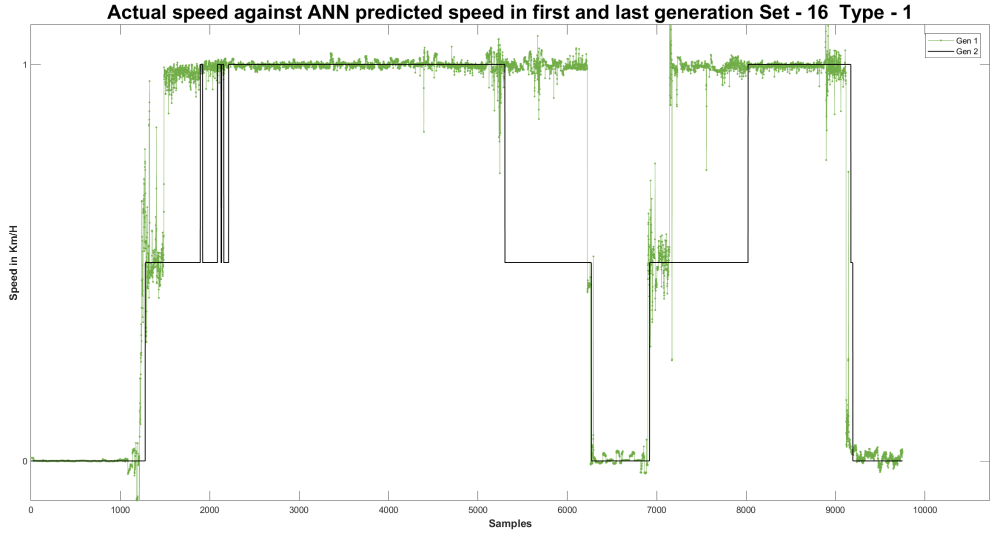
Actual speed against ANN predicted speed in first and last generation Set - 14 Type - 1



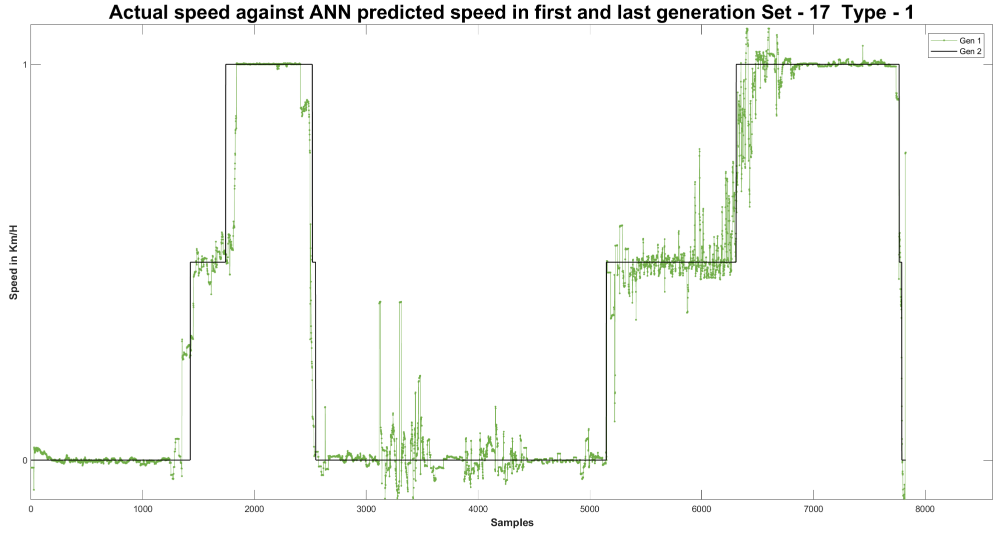
Actual speed against ANN predicted speed in first and last generation Set - 15 Type - 1



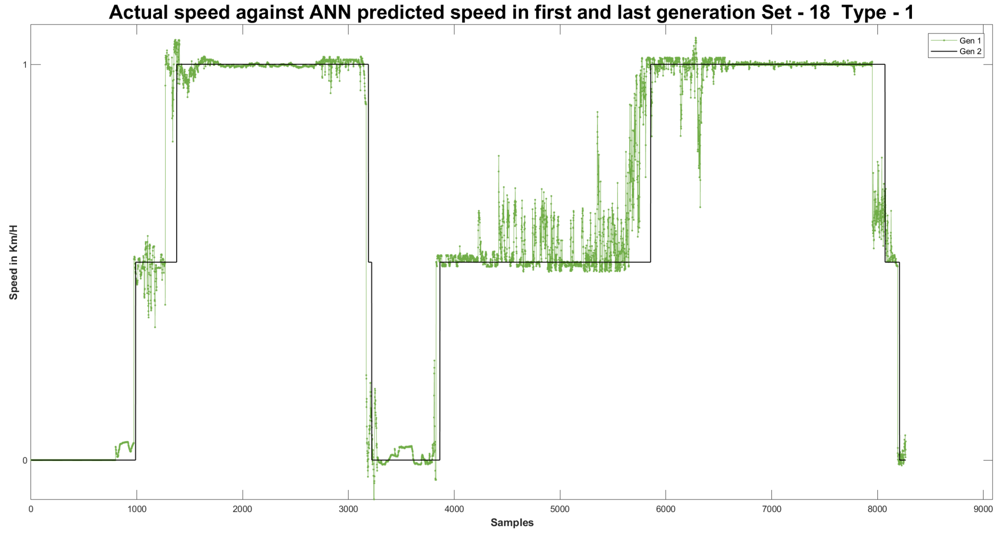
Actual speed against ANN predicted speed in first and last generation Set - 16 Type - 1



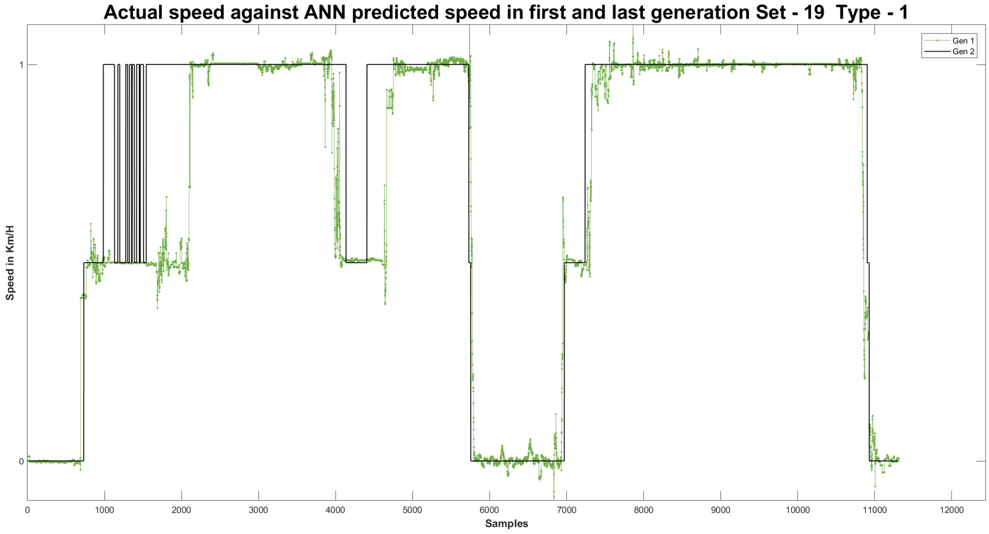
Actual speed against ANN predicted speed in first and last generation Set - 17 Type - 1



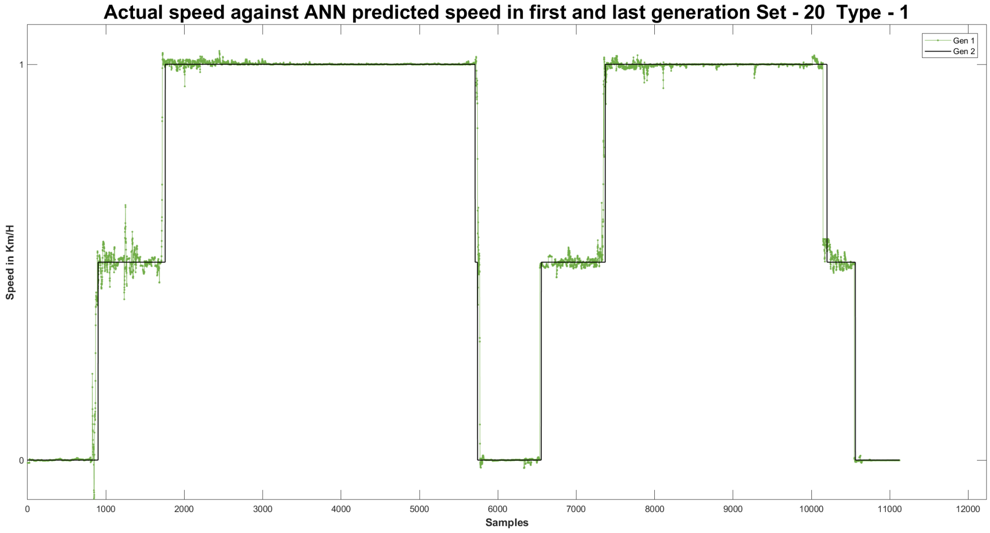
Actual speed against ANN predicted speed in first and last generation Set - 18 Type - 1



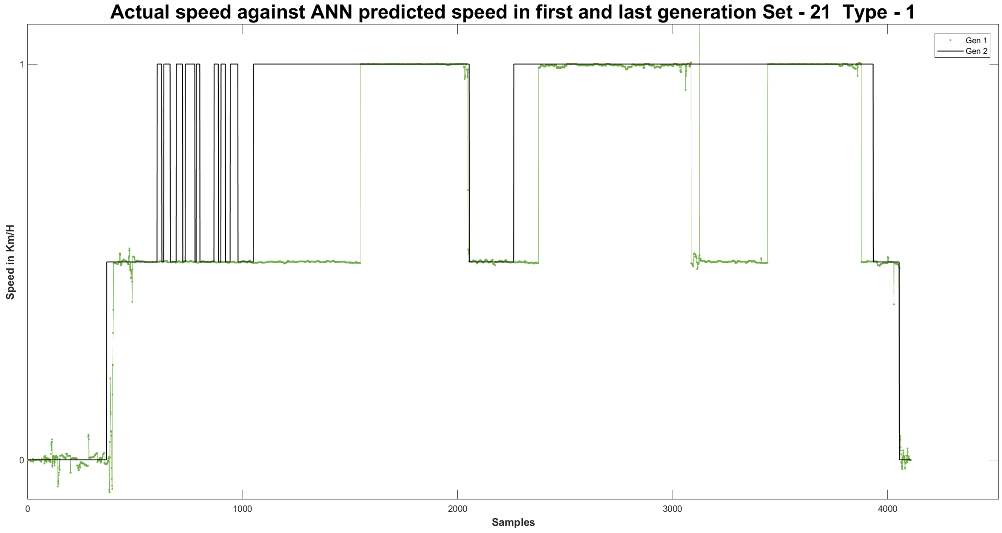
Actual speed against ANN predicted speed in first and last generation Set - 19 Type - 1

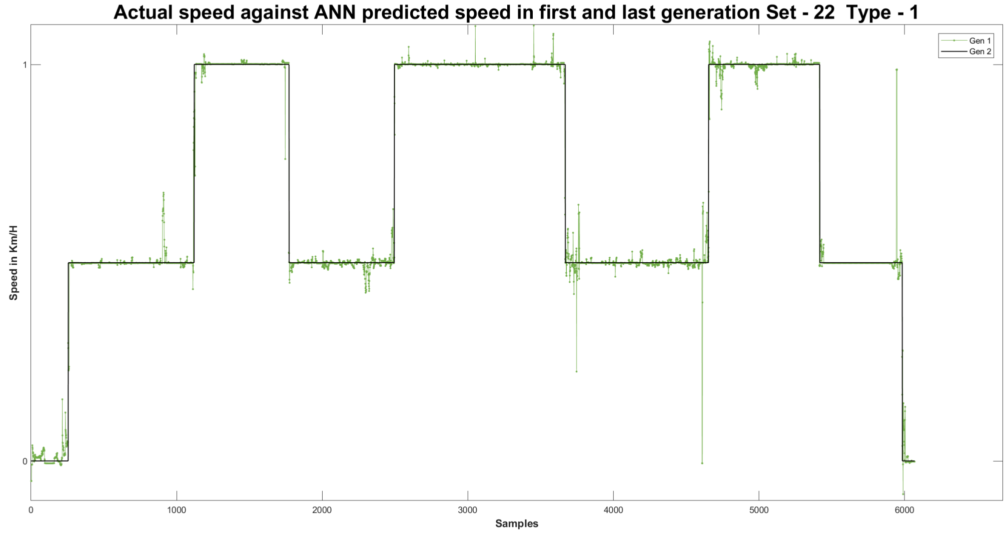


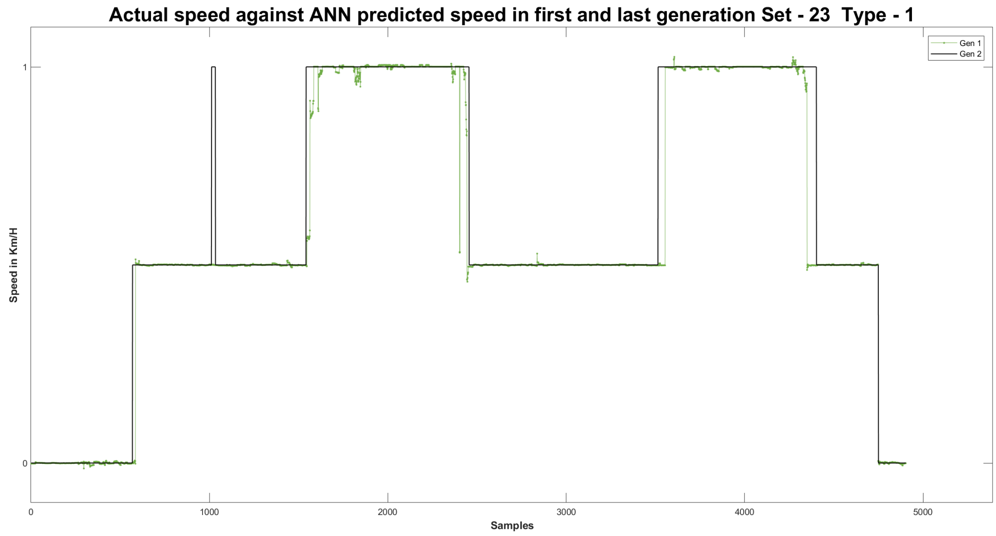
Actual speed against ANN predicted speed in first and last generation Set - 20 Type - 1

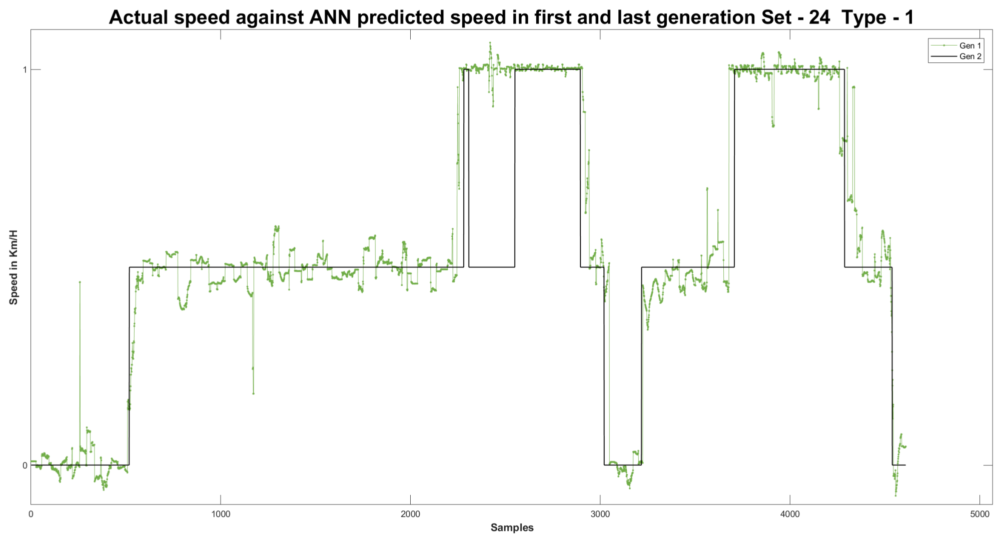


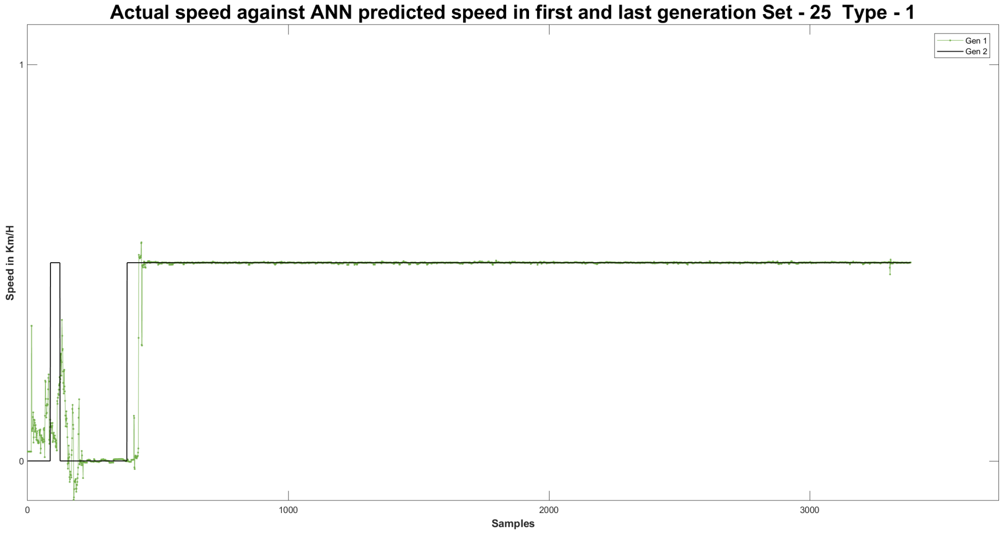
Actual speed against ANN predicted speed in first and last generation Set - 21 Type - 1

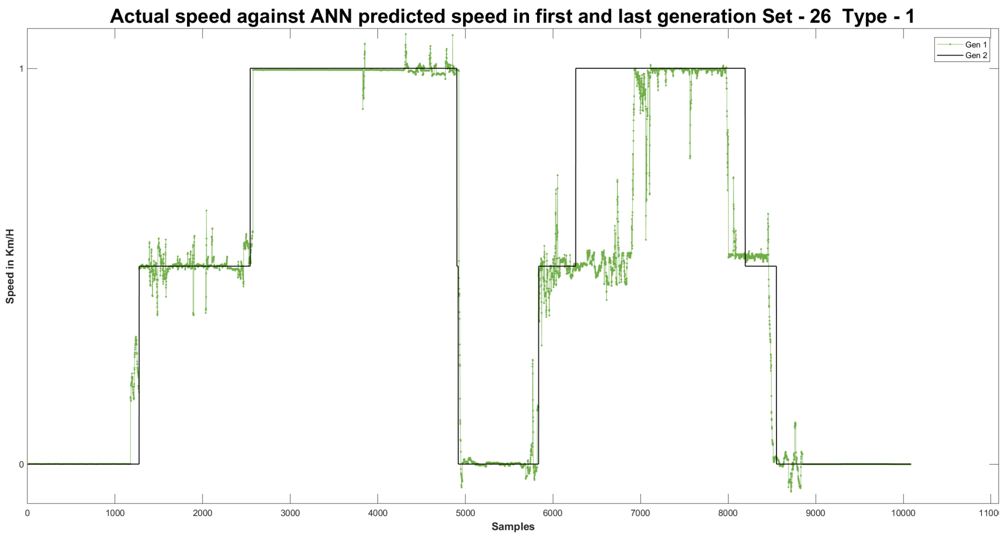


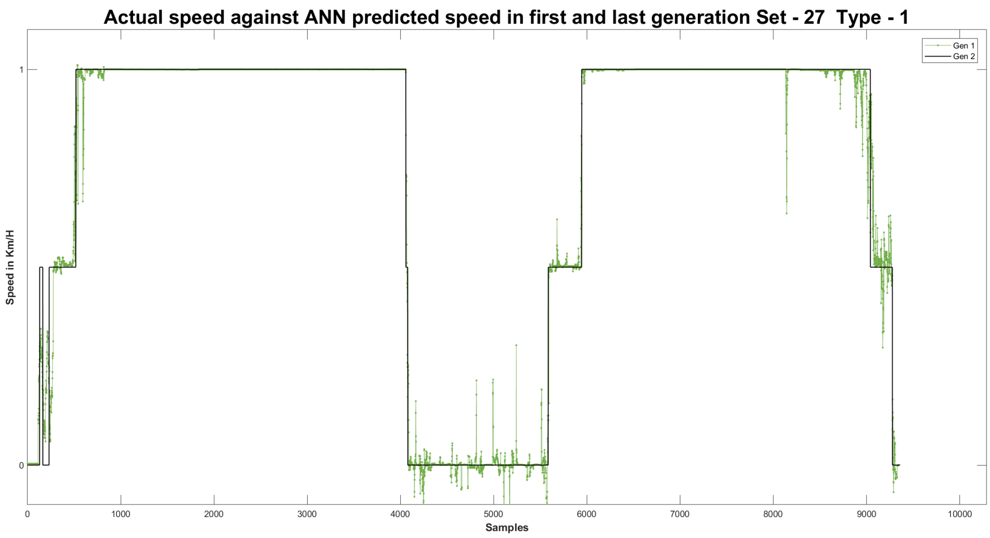

Actual speed against ANN predicted speed in first and last generation Set - 22 Type - 1
Gen 1
Gen 2
Speed in Km/H
1
0
0
1000
2000
3000
4000
5000
6000
Samples


Actual speed against ANN predicted speed in first and last generation Set - 23 Type - 1
Gen 1
Gen 2
Speed in Km/H
1
0
0
1000
2000
3000
4000
5000
Samples


Actual speed against ANN predicted speed in first and last generation Set - 24 Type - 1
Gen 1
Gen 2
Speed in Km/H
1
0
0
1000
2000
3000
4000
5000
Samples


Actual speed against ANN predicted speed in first and last generation Set - 25 Type - 1
Gen 1
Gen 2
Speed in Km/H
Samples
0
1
0
1000
2000
3000


Actual speed against ANN predicted speed in first and last generation Set - 26 Type - 1
Gen 1
Gen 2
Speed in Km/H
Samples
0
1
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

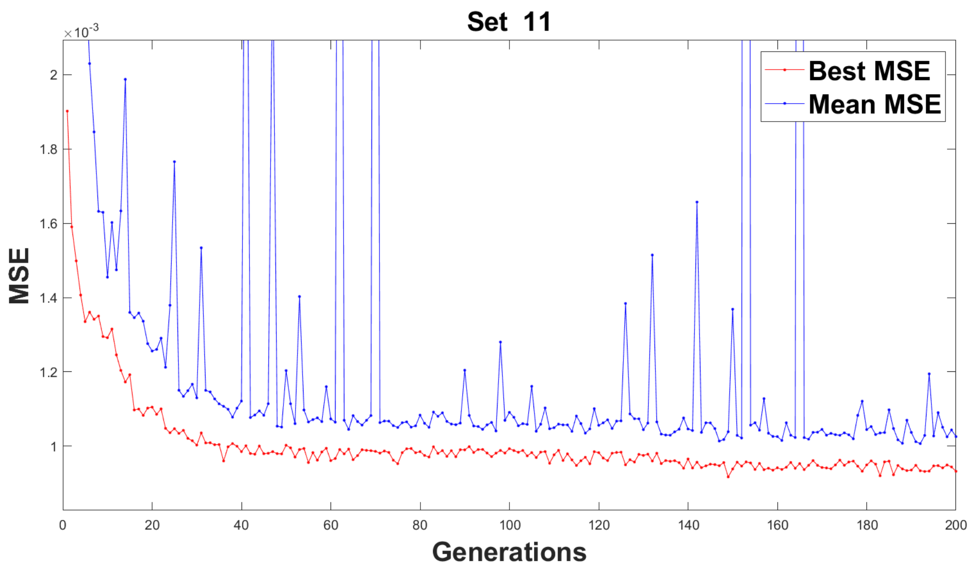

Actual speed against ANN predicted speed in first and last generation Set - 27 Type - 1
Gen 1
Gen 2
Speed in Km/H
Samples
0
1
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000

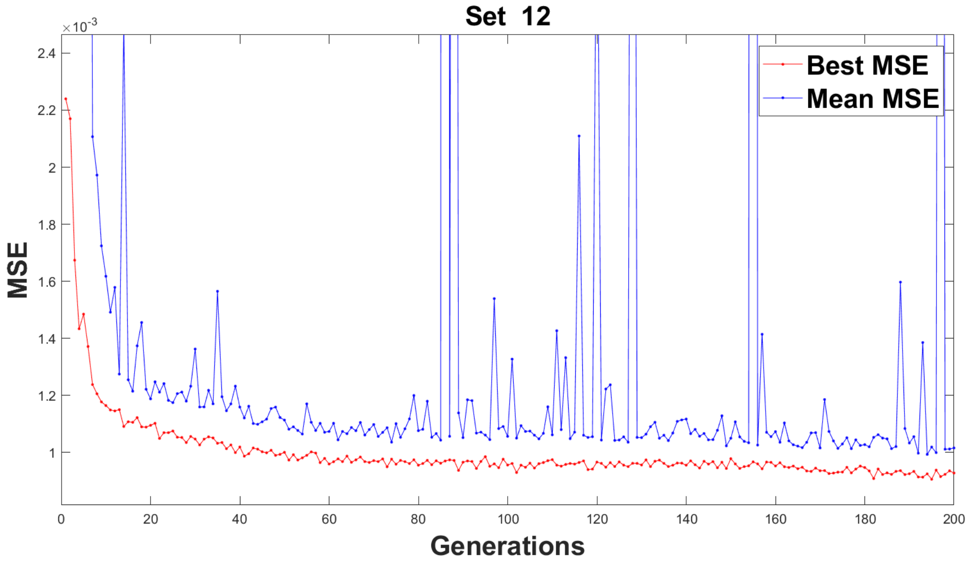
Appendix E

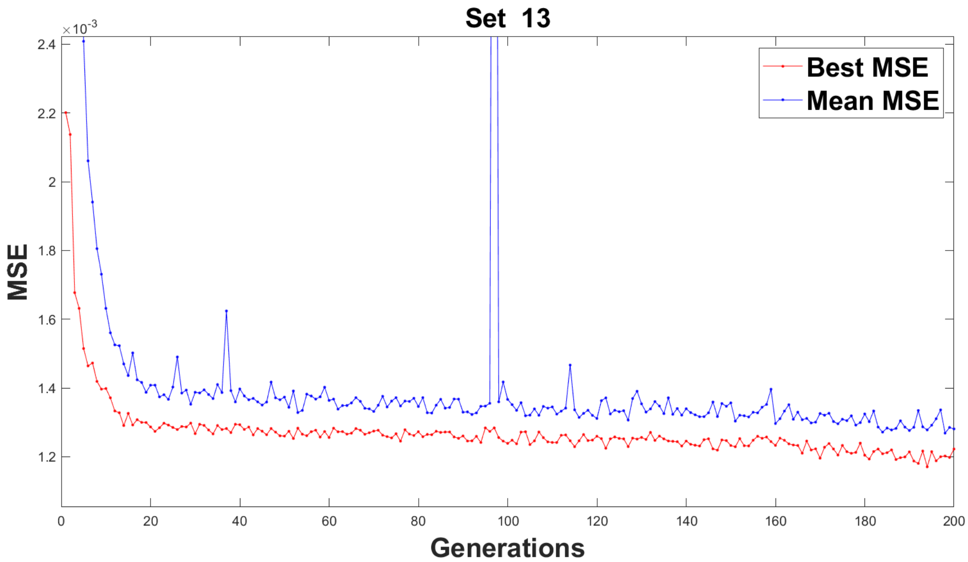
Graphs of MSE over 200 generations of evolution

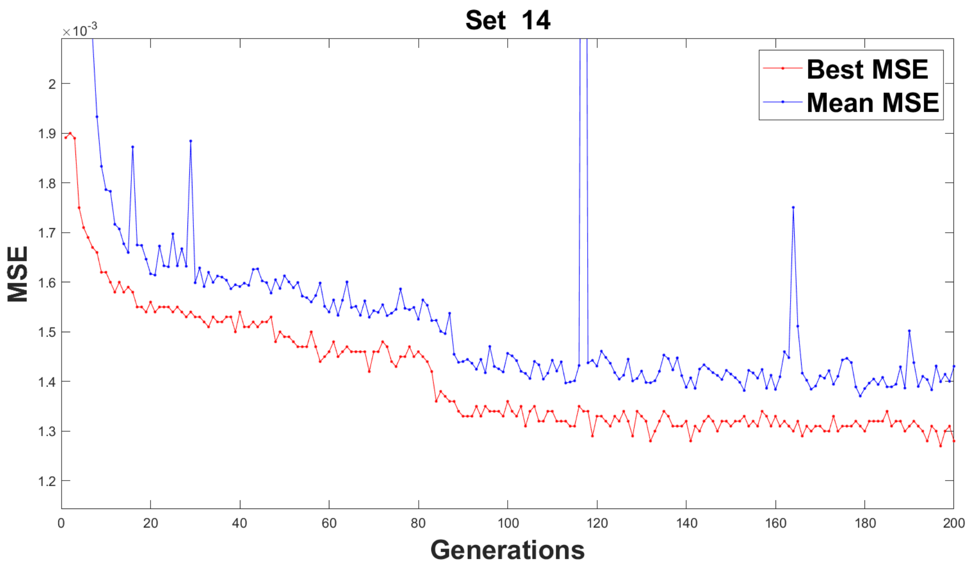
The following diagrams show the evolution of each GA over 200 generation for all 17 sets of data for both speed estimation and movement state.

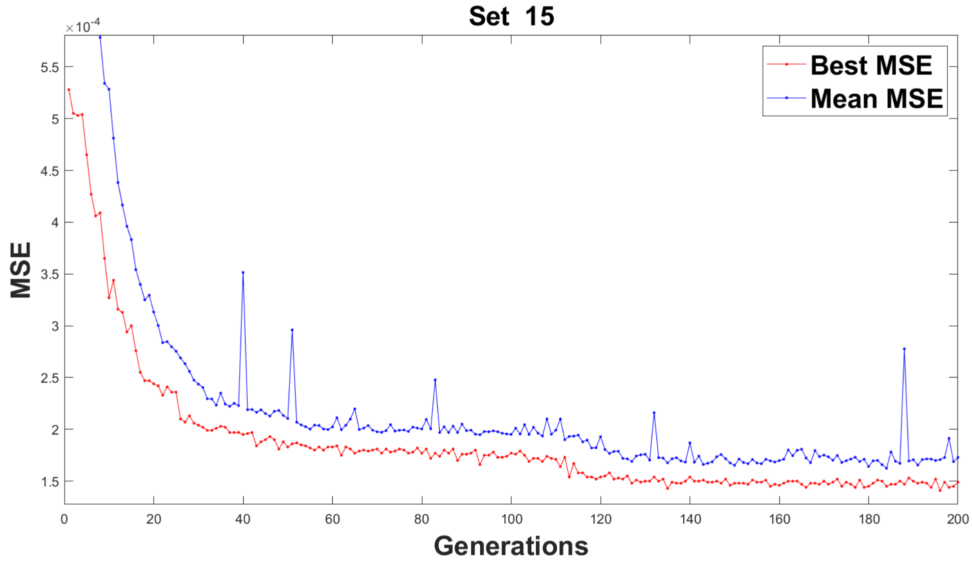
E.1 Speed Estimation

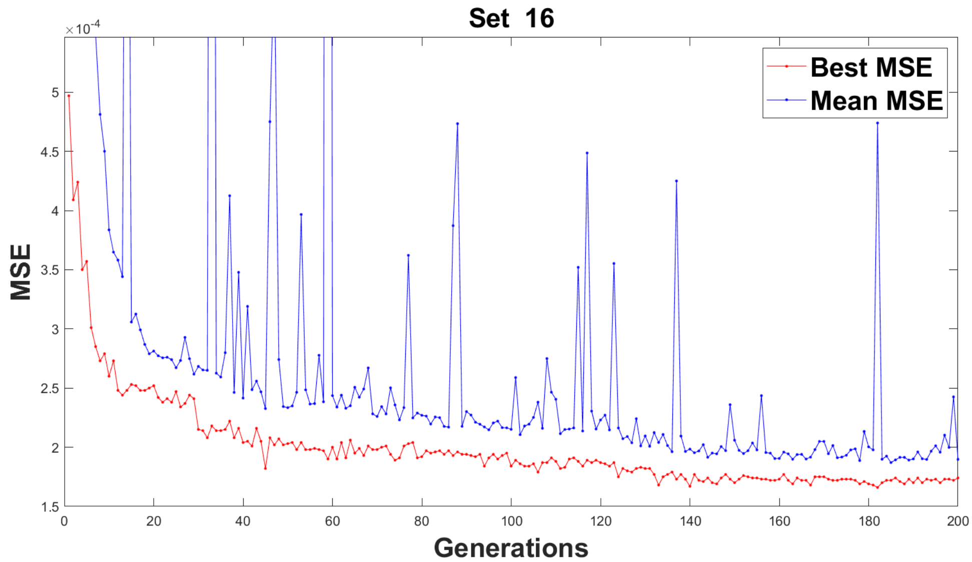


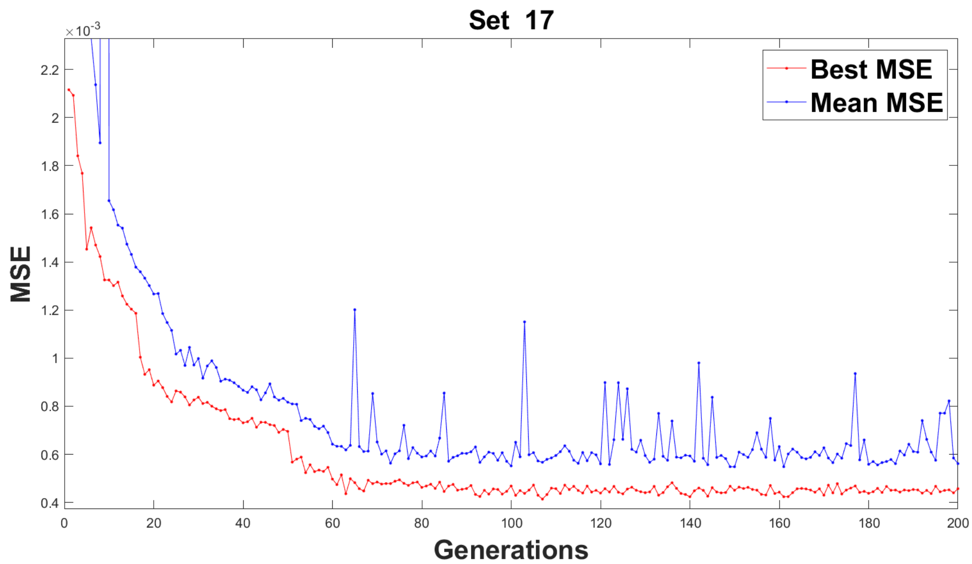

Set 12
×10⁻³
MSE
Generations
Best MSE
Mean MSE

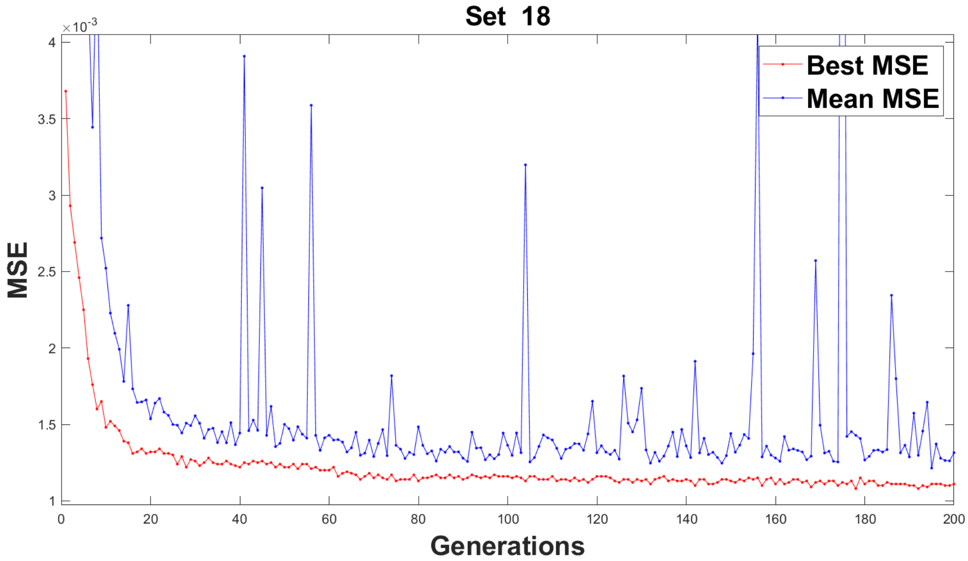

Set 13
×10⁻³
MSE
Generations
Best MSE
Mean MSE

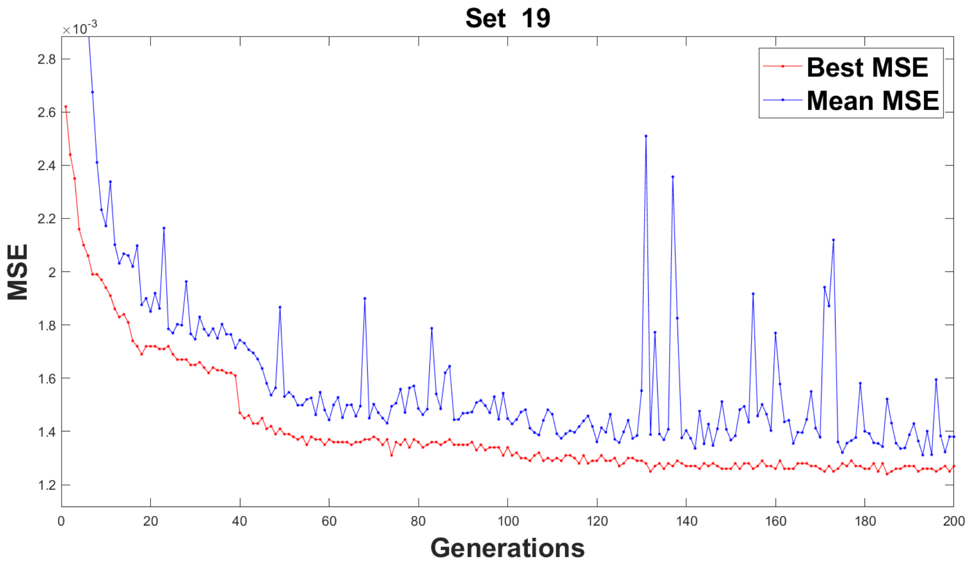

Set 14
×10⁻³
MSE
Generations
Best MSE
Mean MSE

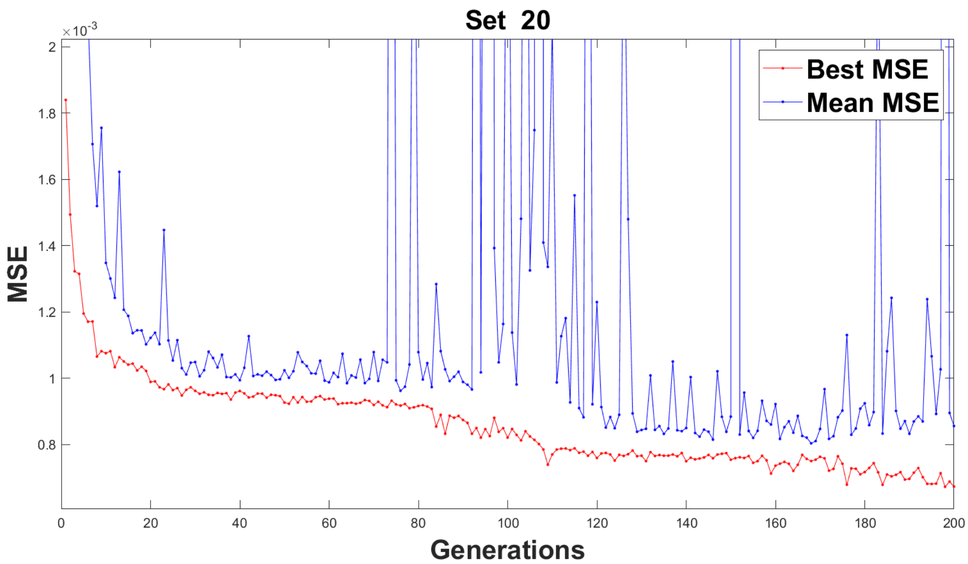

Set 15
×10^-4
MSE
Generations
Best MSE
Mean MSE
5.5
5
4.5
4
3.5
3
2.5
2
1.5
0
20
40
60
80
100
120
140
160
180
200

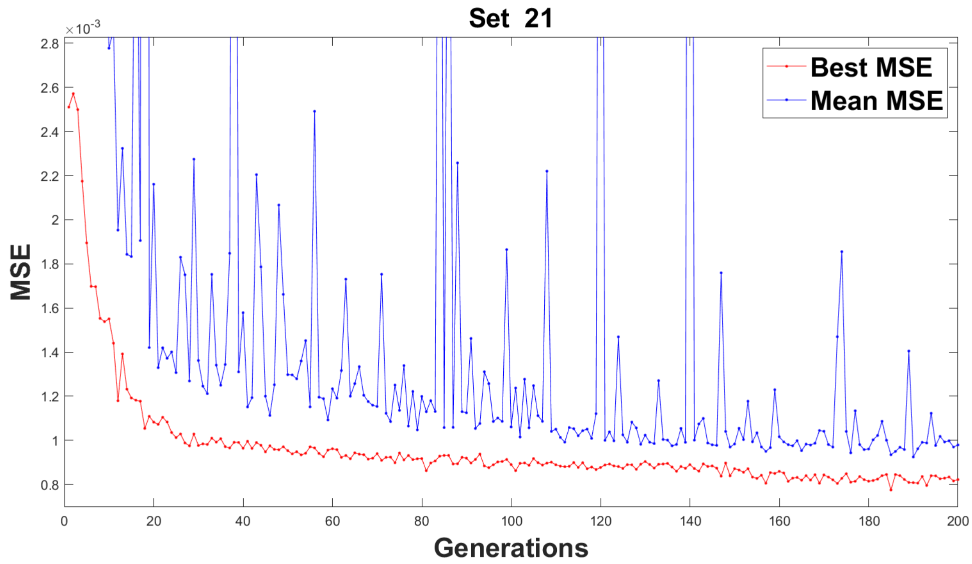

Set 16
×10^-4
MSE
Generations
Best MSE
Mean MSE
5
4.5
4
3.5
3
2.5
2
1.5
0
20
40
60
80
100
120
140
160
180
200

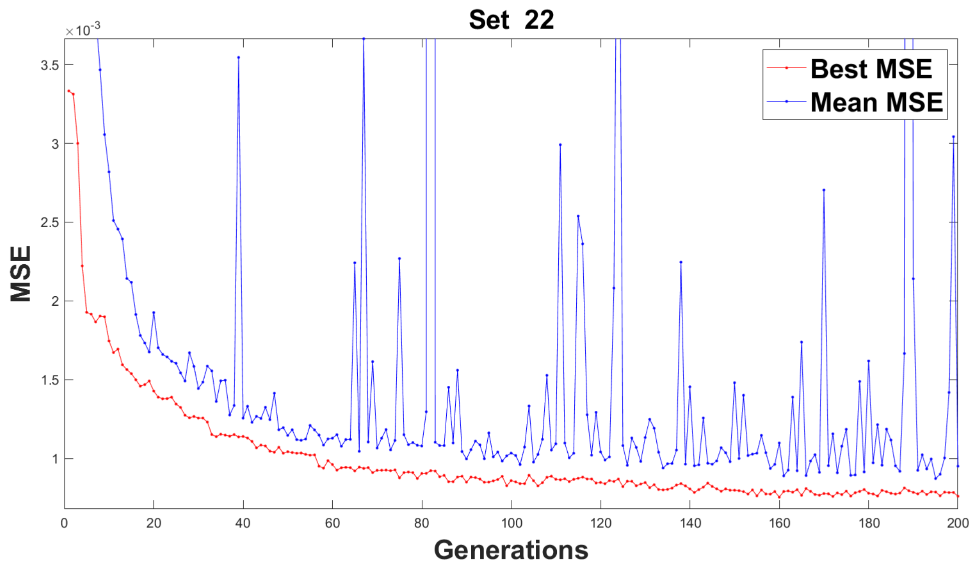

Set 17
×10^-3
MSE
Generations
Best MSE
Mean MSE
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0
20
40
60
80
100
120
140
160
180
200

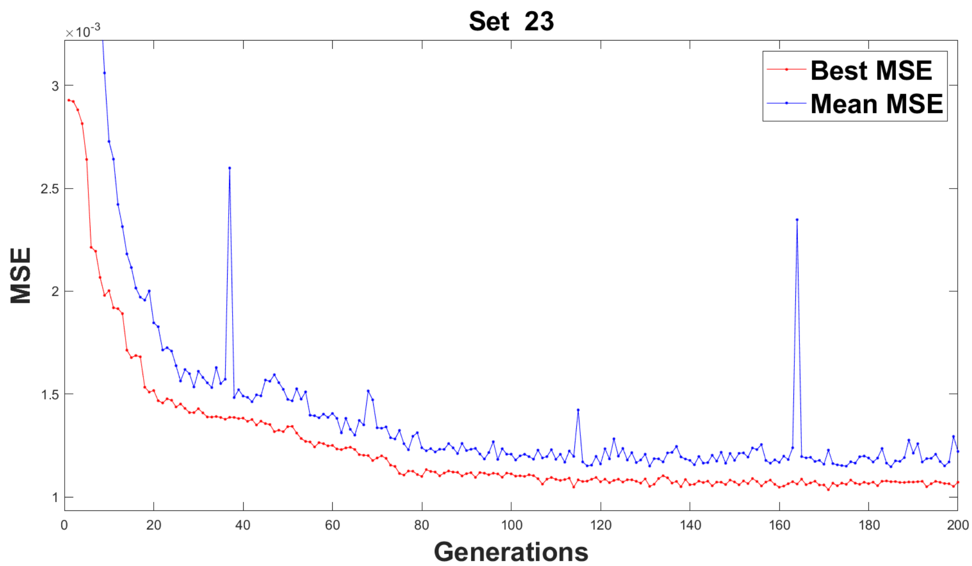

Set 18
×10-3
MSE
Generations
Best MSE
Mean MSE

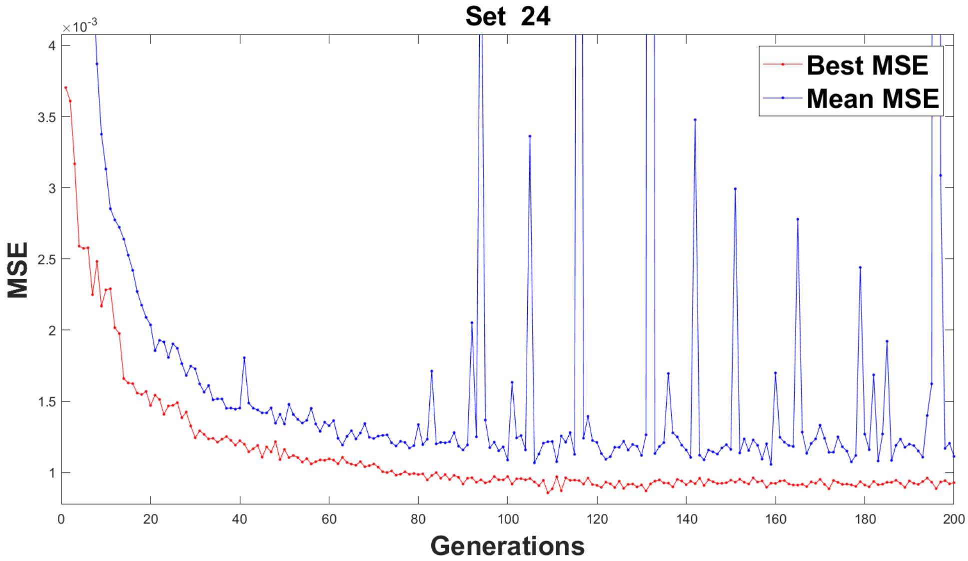

Set 19
×10-3
MSE
Generations
Best MSE
Mean MSE

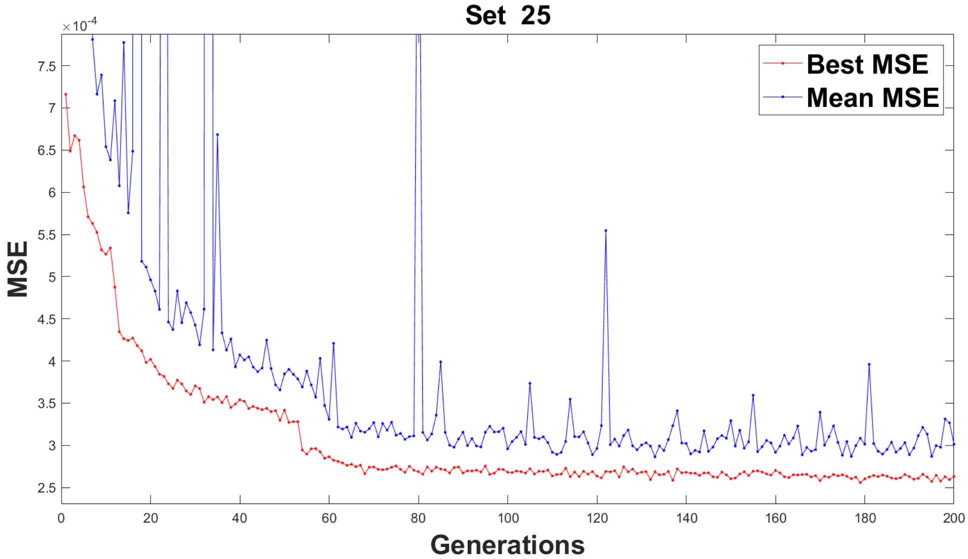

Set 20
×10-3
MSE
Generations
Best MSE
Mean MSE

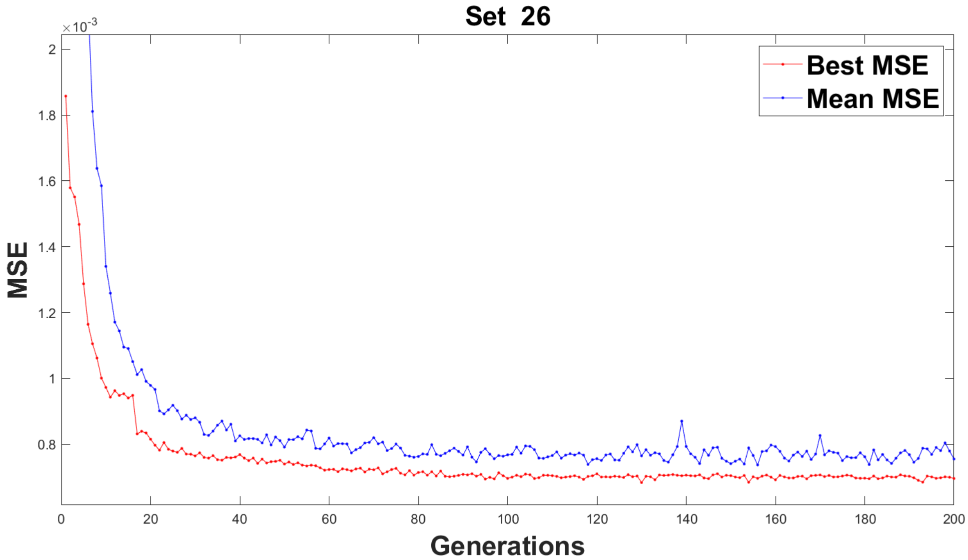

Set 21
×10⁻³
2.8
2.6
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
MSE
0
20
40
60
80
100
120
140
160
180
200
Generations
Best MSE
Mean MSE

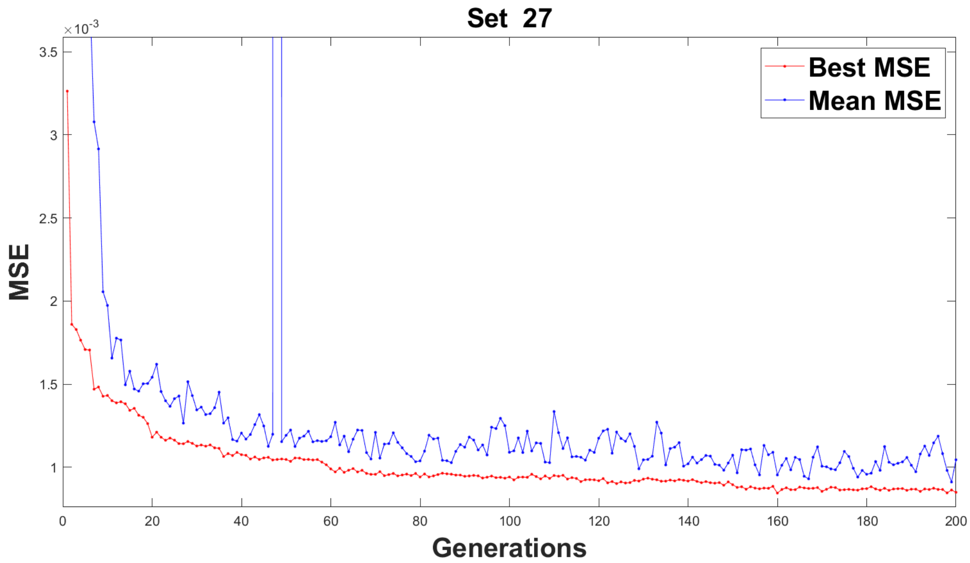

Set 22
×10⁻³
3.5
3
2.5
2
1.5
1
MSE
0
20
40
60
80
100
120
140
160
180
200
Generations
Best MSE
Mean MSE


Set 23
×10⁻³
3
2.5
2
1.5
1
MSE
0
20
40
60
80
100
120
140
160
180
200
Generations
Best MSE
Mean MSE

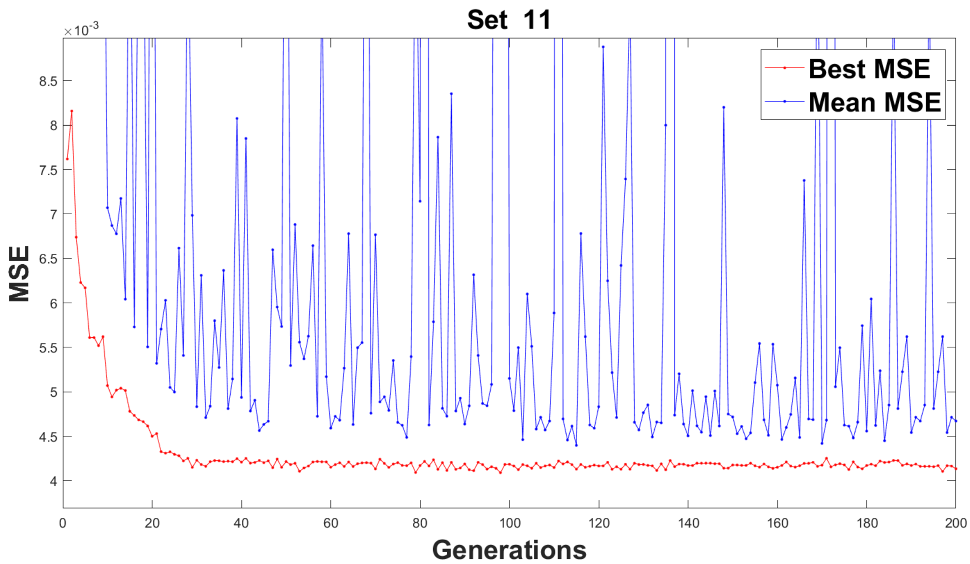

Set 24
×10-3
MSE
Generations
Best MSE
Mean MSE

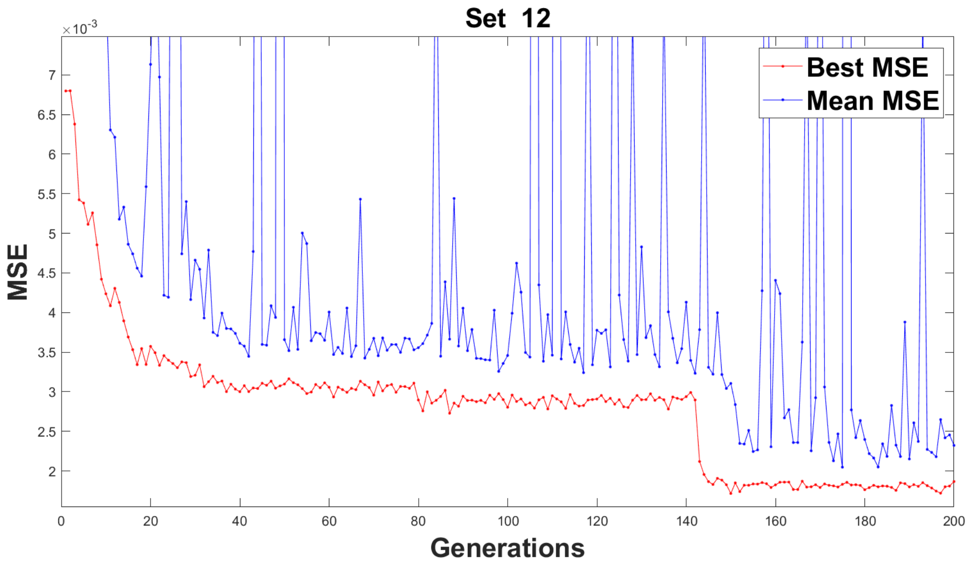

Set 25
×10-4
MSE
Generations
Best MSE
Mean MSE

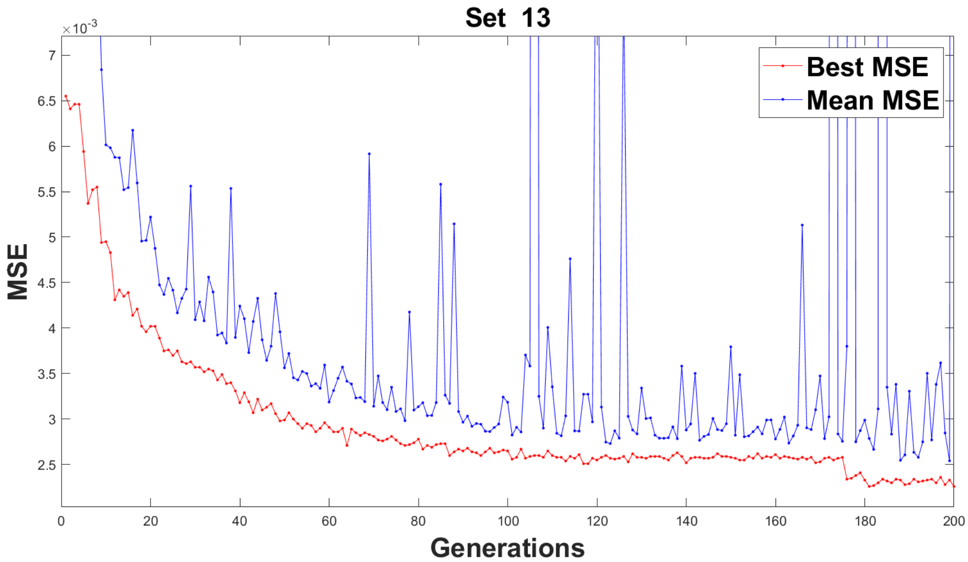

Set 26
×10-3
MSE
Generations
Best MSE
Mean MSE

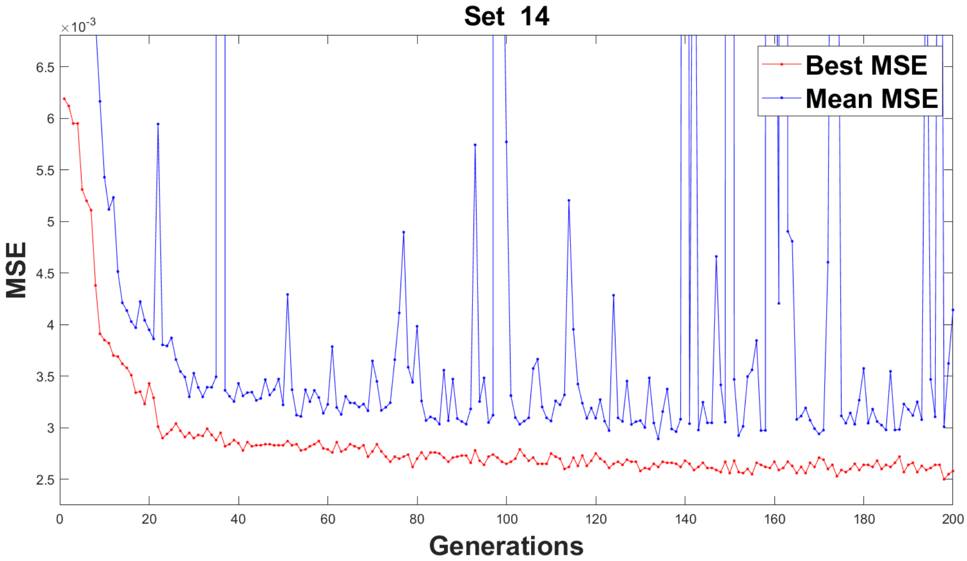


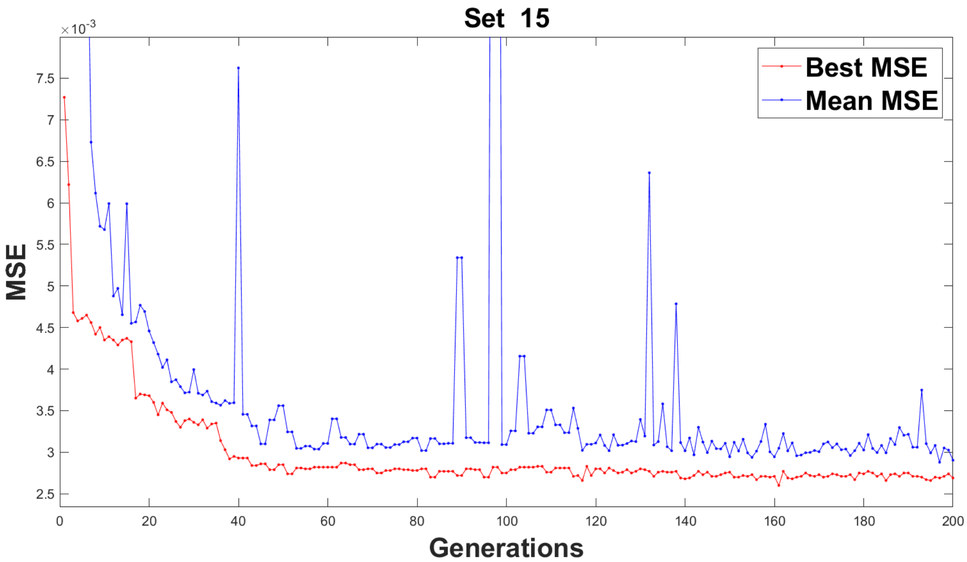
E.2 Movement State Approximation

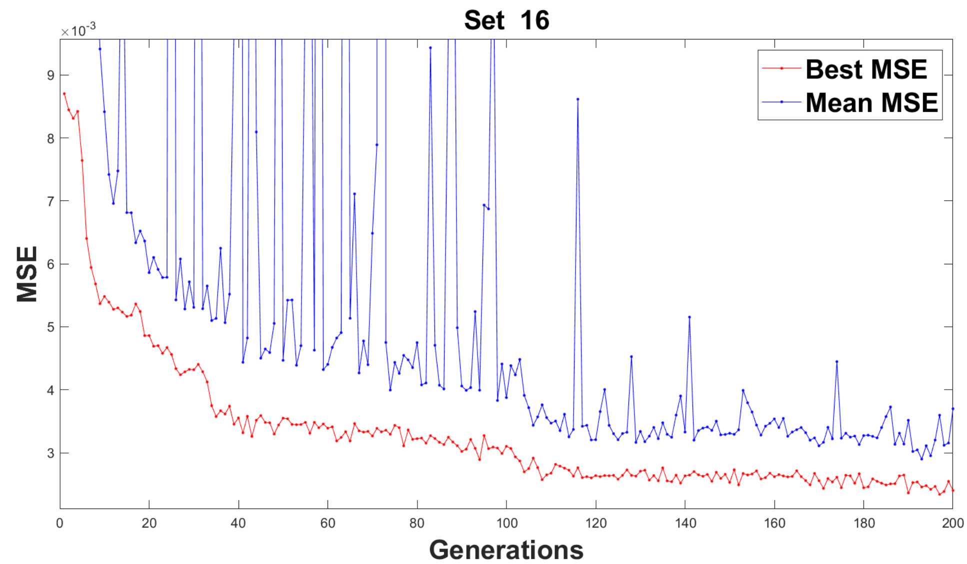


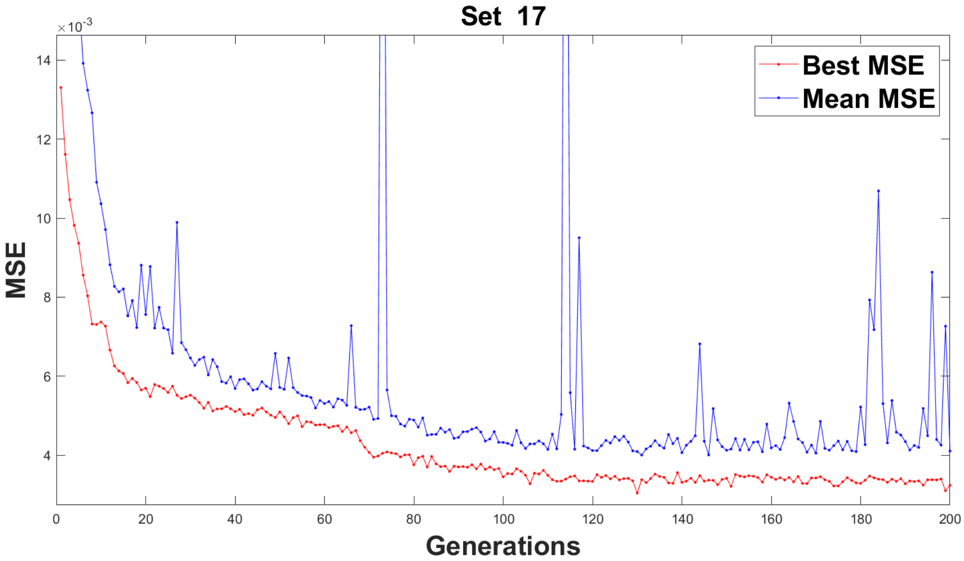

Set 12
×10^-3
MSE
Generations
Best MSE
Mean MSE
0
20
40
60
80
100
120
140
160
180
200
2
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7

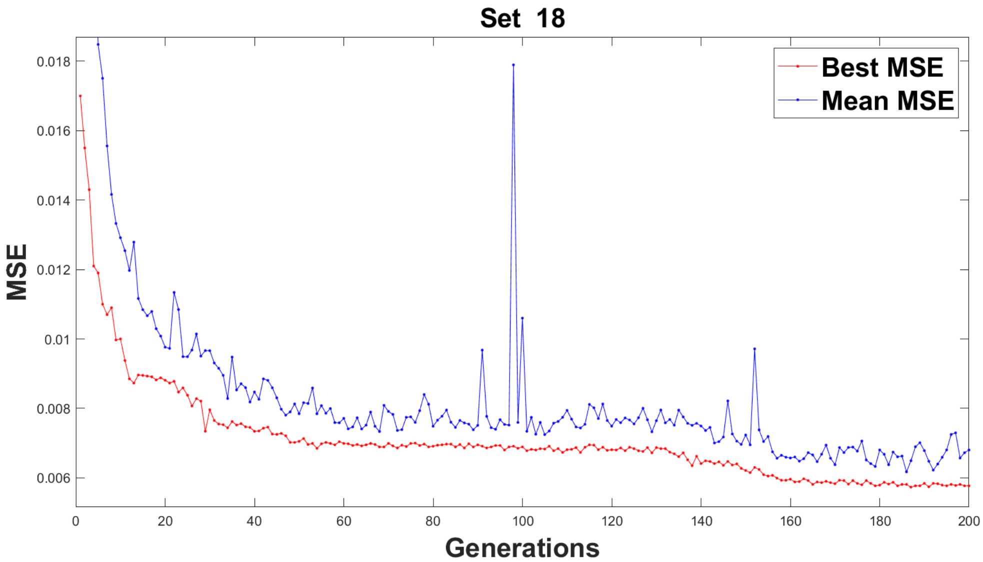

Set 13
×10^-3
MSE
Generations
Best MSE
Mean MSE
0
20
40
60
80
100
120
140
160
180
200
2.5
3
3.5
4
4.5
5
5.5
6
6.5
7

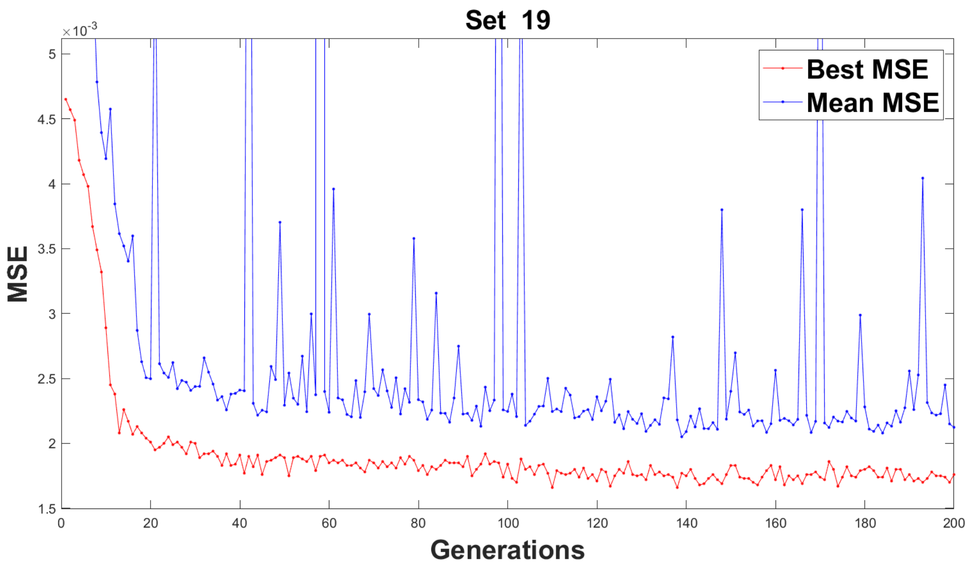

Set 14
×10^-3
MSE
Generations
Best MSE
Mean MSE

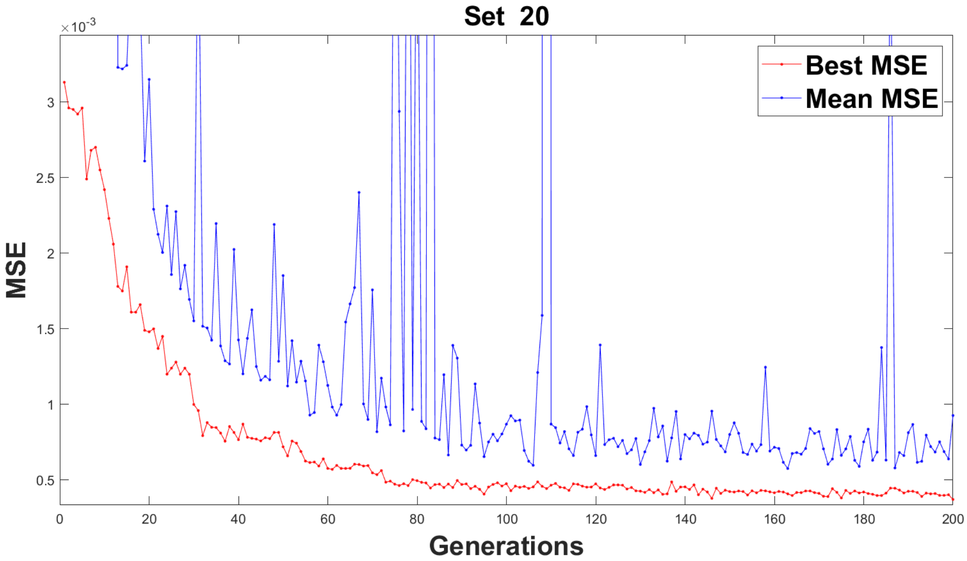

Set 15
×10^-3
MSE
Generations
Best MSE
Mean MSE

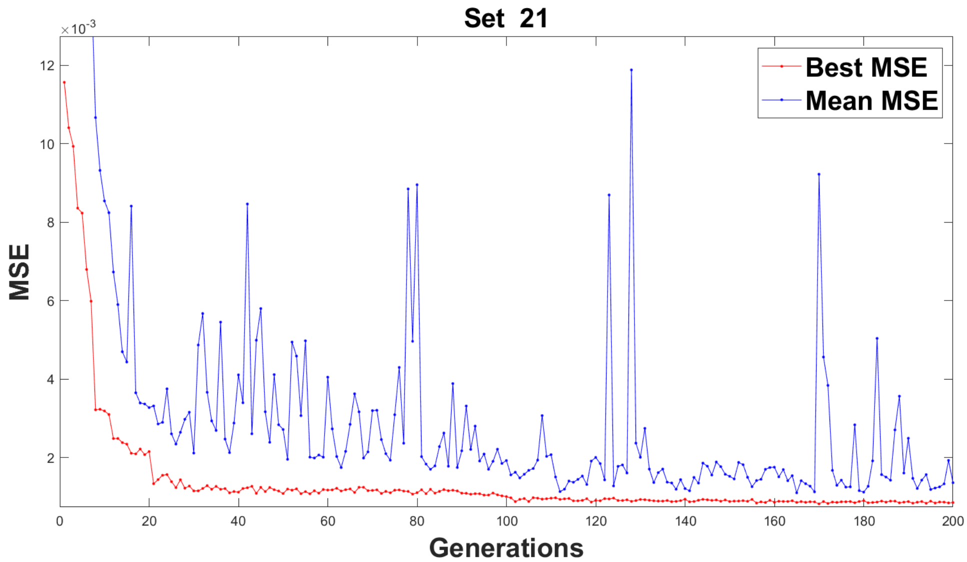

Set 16
×10^-3
MSE
Generations
Best MSE
Mean MSE

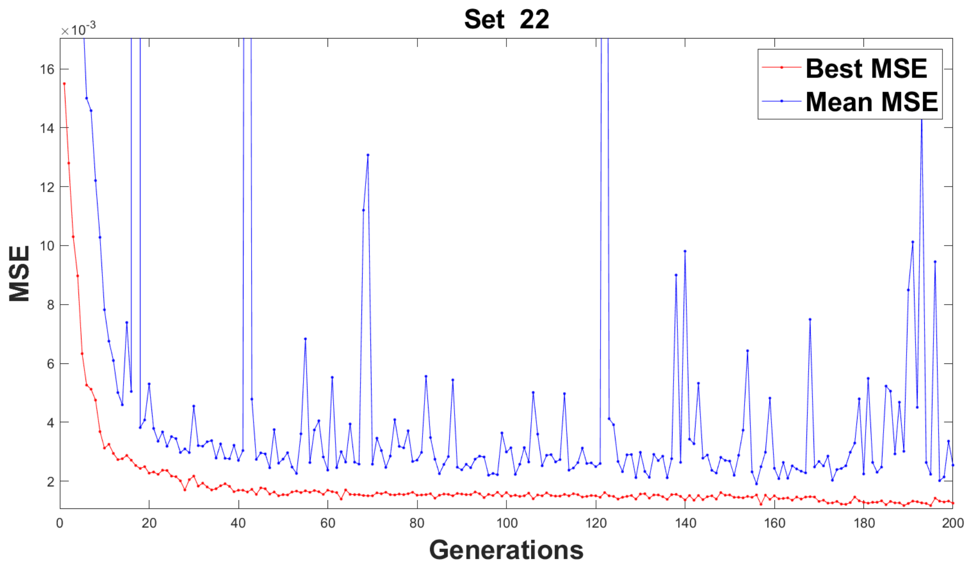

Set 17
×10-3
MSE
Generations
Best MSE
Mean MSE

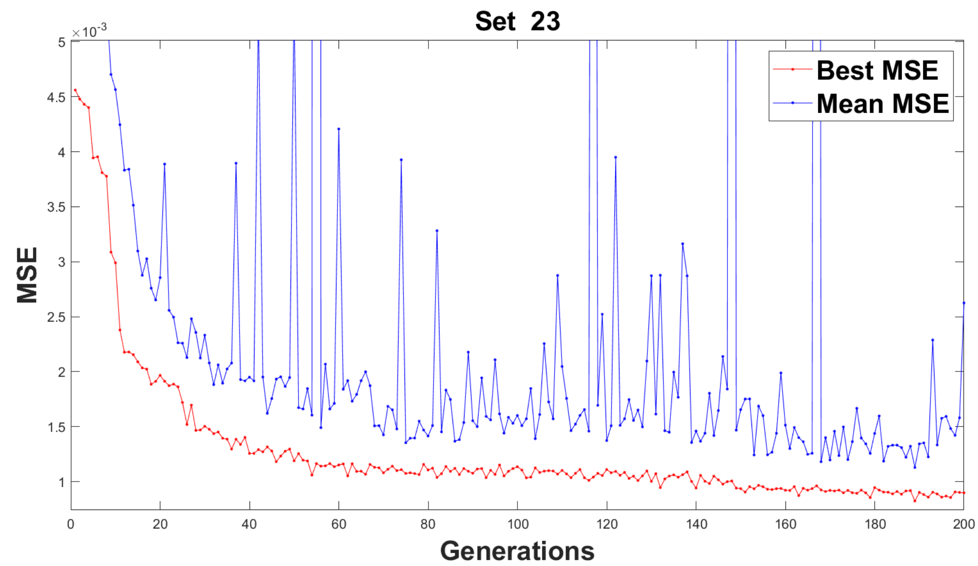

Set 18
MSE
Generations
Best MSE
Mean MSE

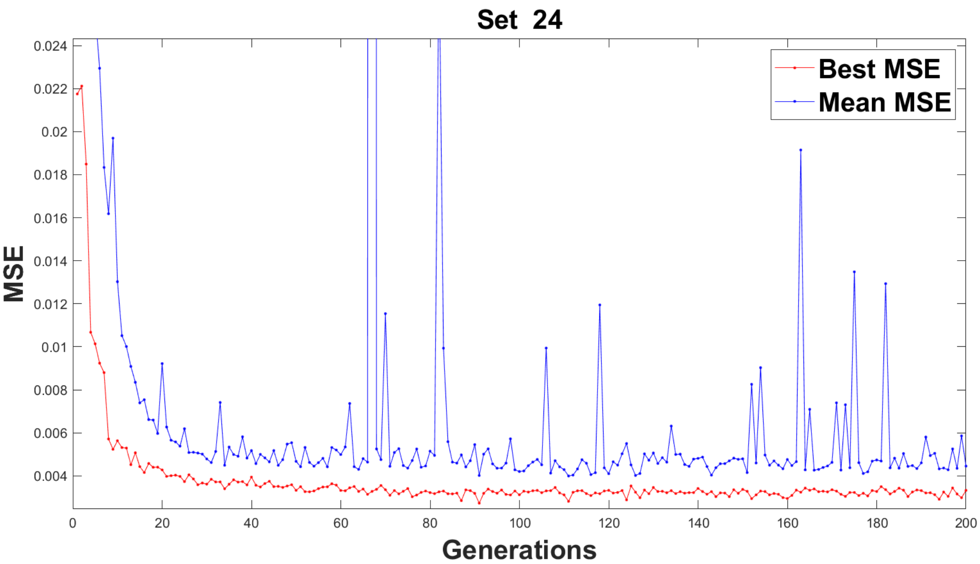

Set 19
×10-3
MSE
Generations
Best MSE
Mean MSE

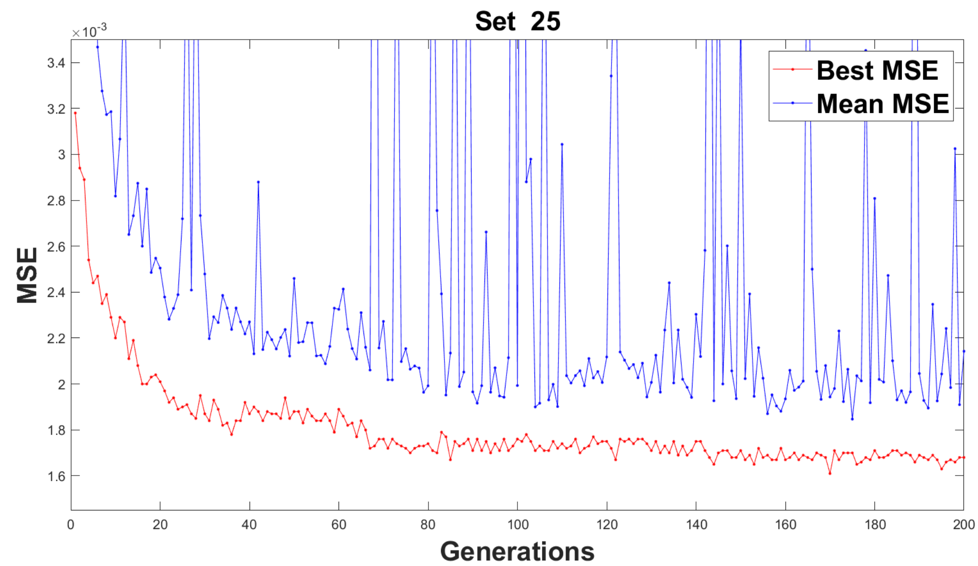

Set 20
×10^-3
MSE
Generations
Best MSE
Mean MSE
0
20
40
60
80
100
120
140
160
180
200
0.5
1
1.5
2
2.5
3

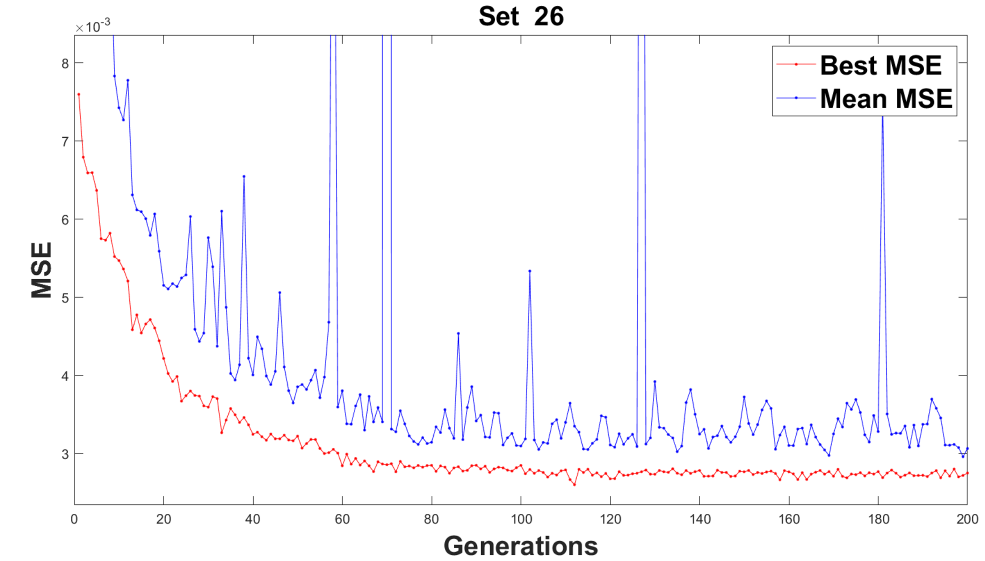

Set 21
×10^-3
MSE
Generations
Best MSE
Mean MSE
0
20
40
60
80
100
120
140
160
180
200
2
4
6
8
10
12

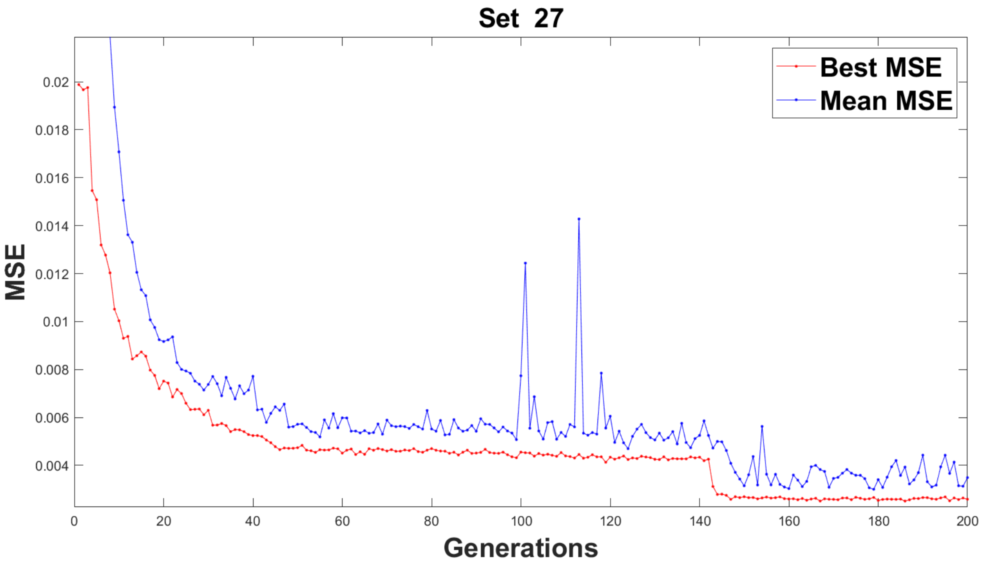

Set 22
×10^-3
MSE
Generations
Best MSE
Mean MSE
0
20
40
60
80
100
120
140
160
180
200
2
4
6
8
10
12
14
16


Set 23
×10^-3
MSE
Generations
Best MSE
Mean MSE


Set 24
MSE
Generations
Best MSE
Mean MSE


Set 25
×10^-3
MSE
Generations
Best MSE
Mean MSE


Set 26
×10^-3
8
7
6
5
4
3
MSE
0
20
40
60
80
100
120
140
160
180
200
Generations
Best MSE
Mean MSE

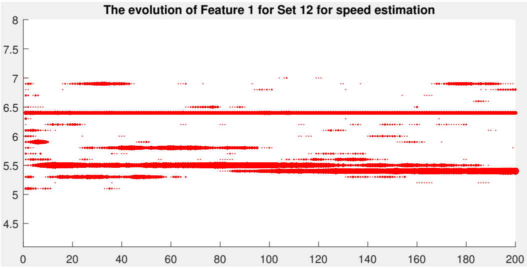

Set 27
0.02
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
MSE
0
20
40
60
80
100
120
140
160
180
200
Generations
Best MSE
Mean MSE

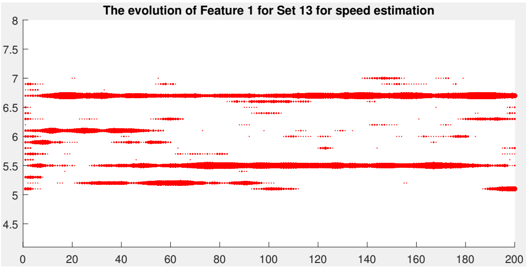
Appendix F

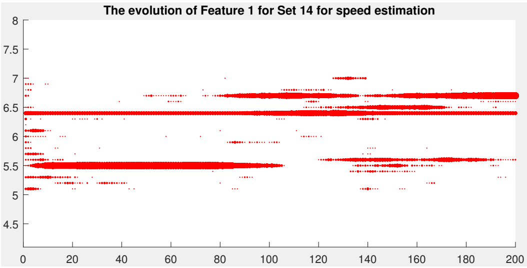
The evolution of one gene for all the sets of data

The following diagrams show the evolution of a selection of genes for every set of data.

F.1 The Evolution of the Walking Speed Gene for All Sets for Speed Estimation

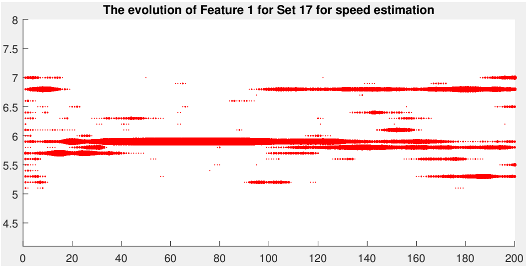


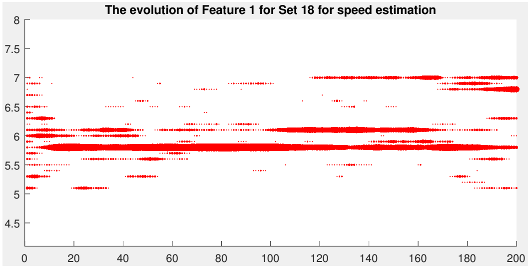


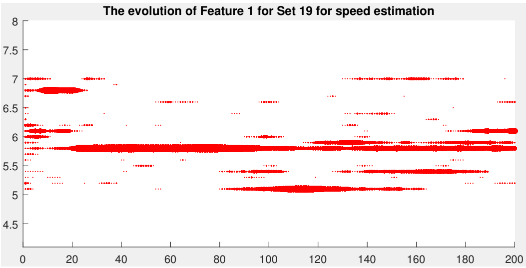



The evolution of Feature 1 for Set 15 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 1 for Set 16 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

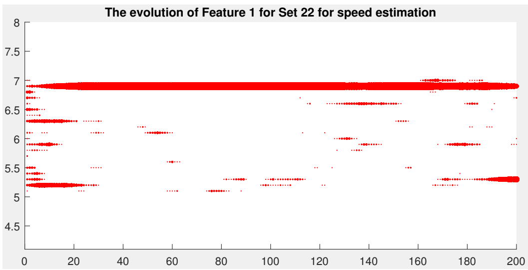

The evolution of Feature 1 for Set 17 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

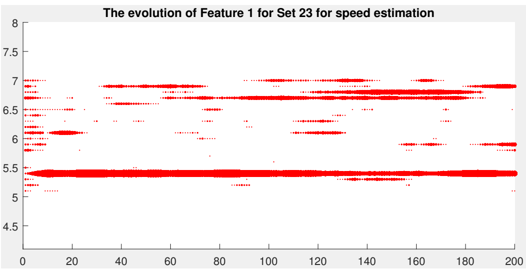

The evolution of Feature 1 for Set 18 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

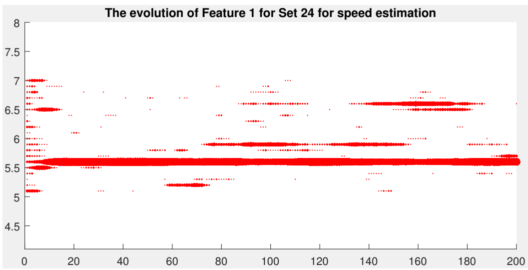

The evolution of Feature 1 for Set 19 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

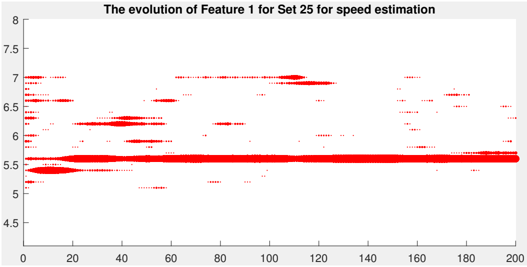

The evolution of Feature 1 for Set 20 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

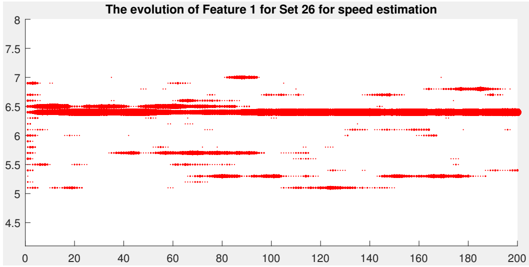

The evolution of Feature 1 for Set 21 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

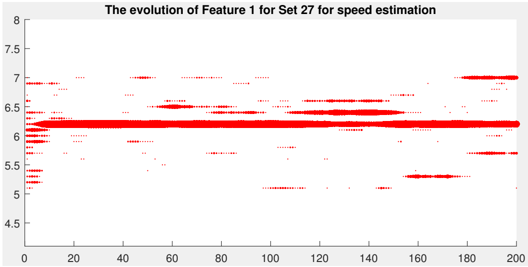

The evolution of Feature 1 for Set 22 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 1 for Set 23 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

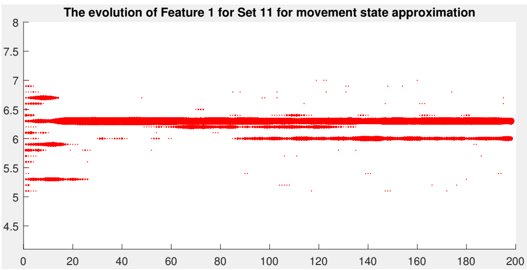

The evolution of Feature 1 for Set 24 for speed estimation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

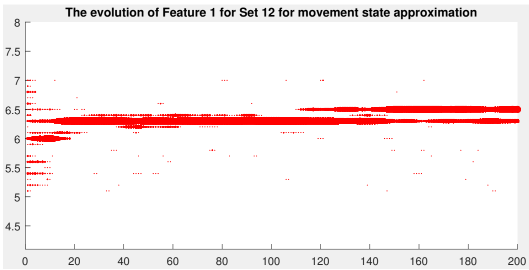


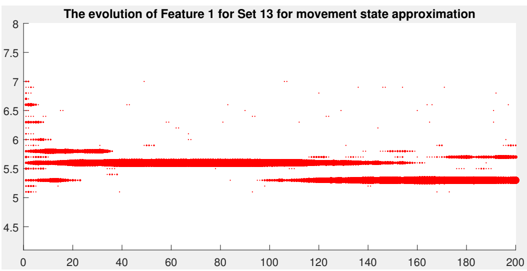


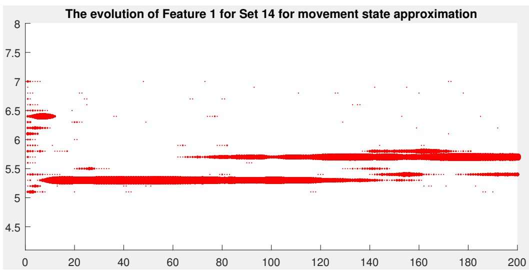


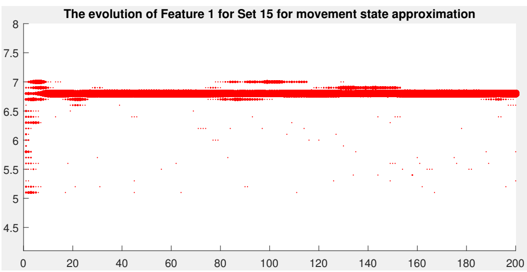
F.2 The Evolution of the Walking Speed Gene for All Sets for Movement State Approximation

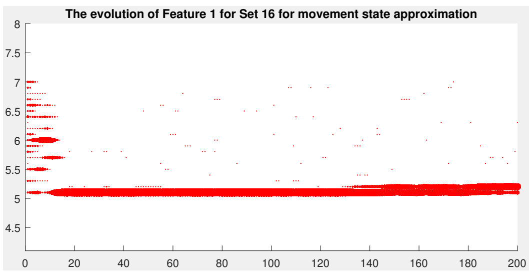


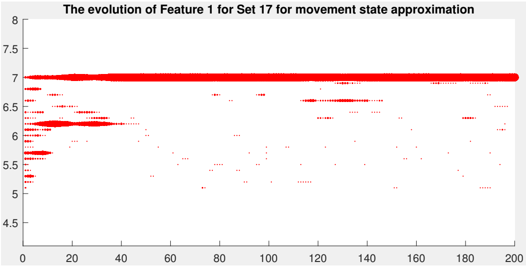


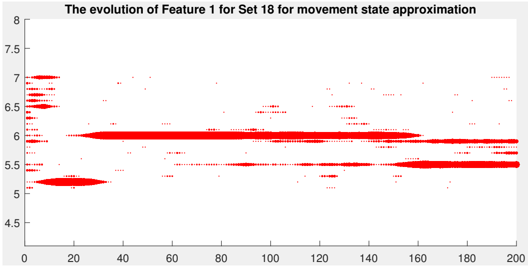


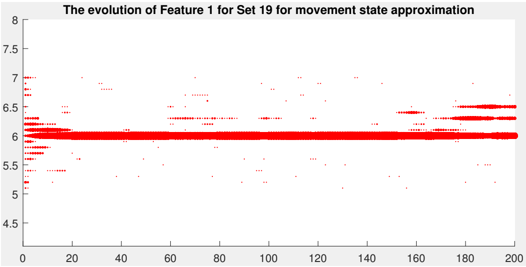


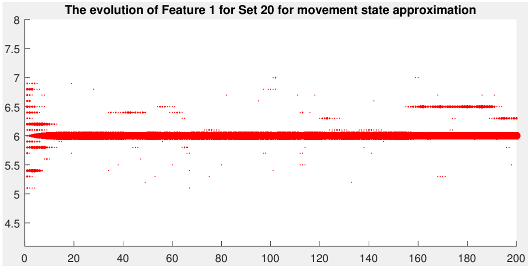


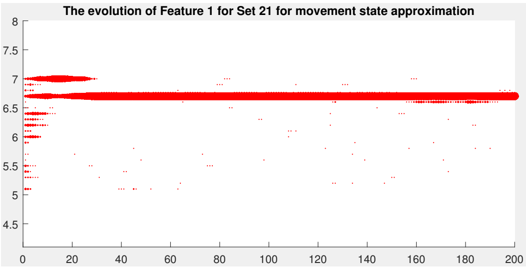


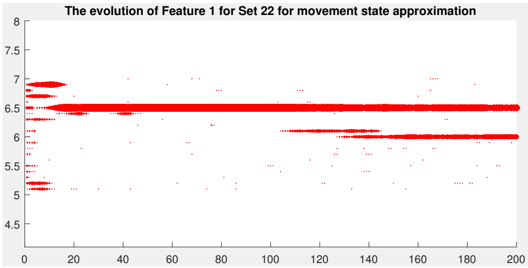

The evolution of Feature 1 for Set 17 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

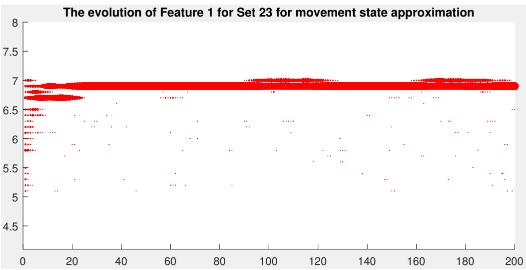

The evolution of Feature 1 for Set 18 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

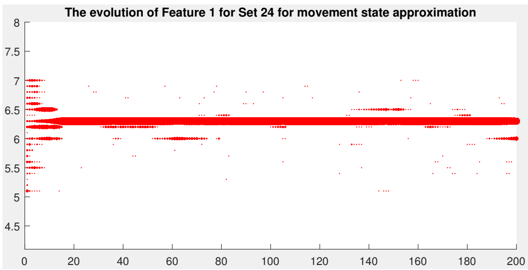

The evolution of Feature 1 for Set 19 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

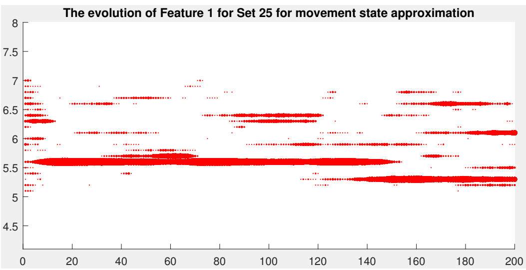

The evolution of Feature 1 for Set 20 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

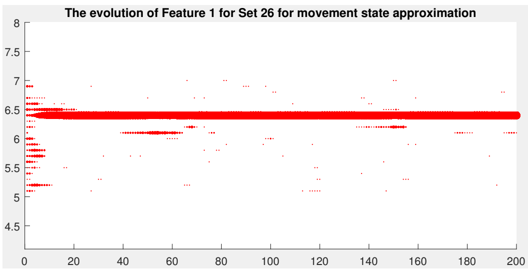

The evolution of Feature 1 for Set 21 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

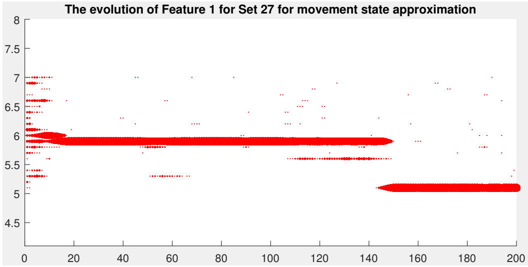

The evolution of Feature 1 for Set 22 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 1 for Set 23 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

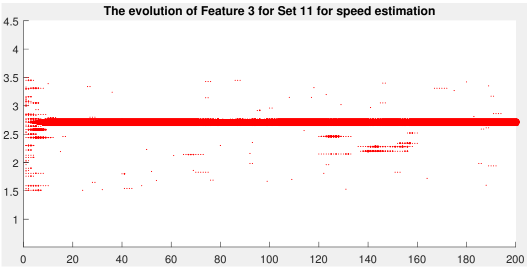

The evolution of Feature 1 for Set 24 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

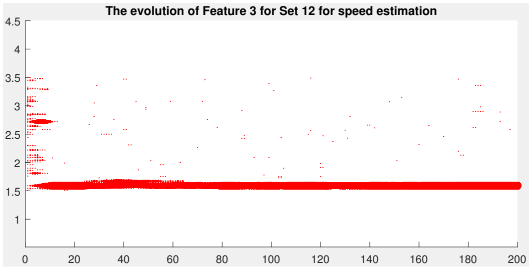

The evolution of Feature 1 for Set 25 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

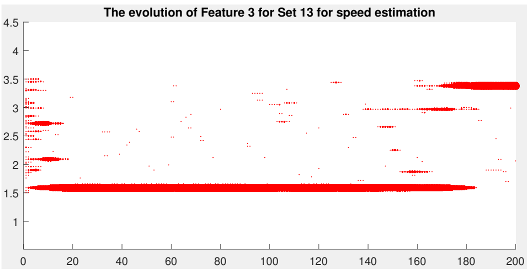

The evolution of Feature 1 for Set 26 for movement state approximation
8
7.5
7
6.5
6
5.5
5
4.5
0 20 40 60 80 100 120 140 160 180 200

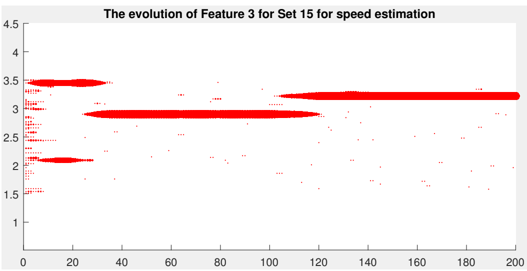


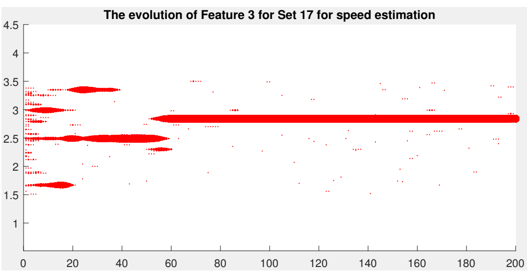
F.3 The Evolution of the Spike Size Gene for All Sets for Speed Estimation

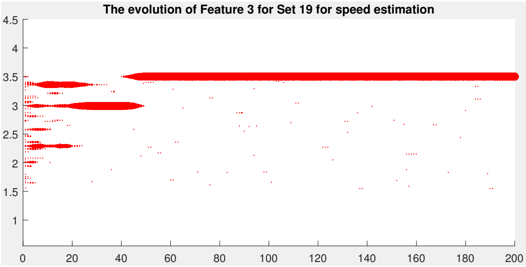


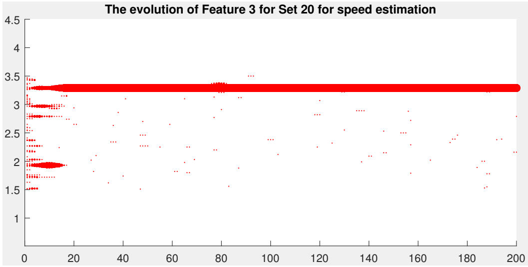


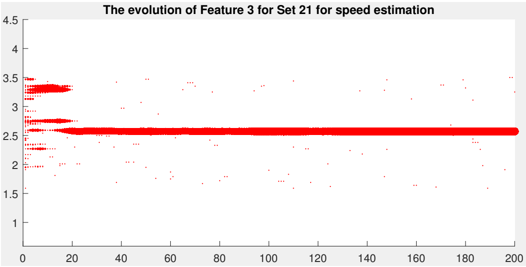


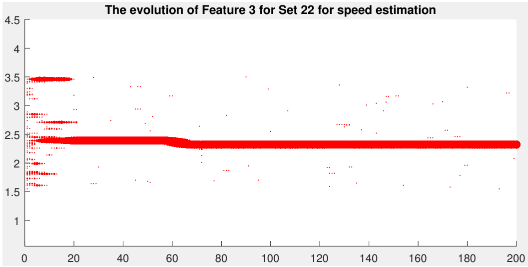


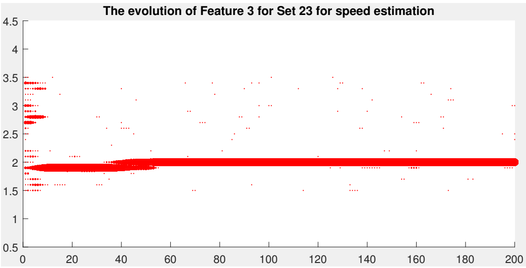


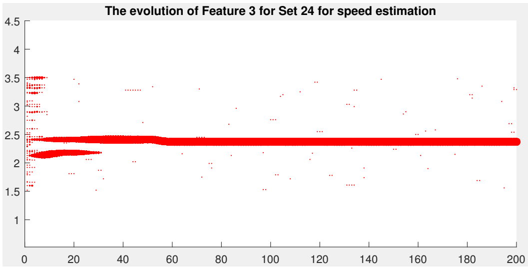

The evolution of Feature 3 for Set 19 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

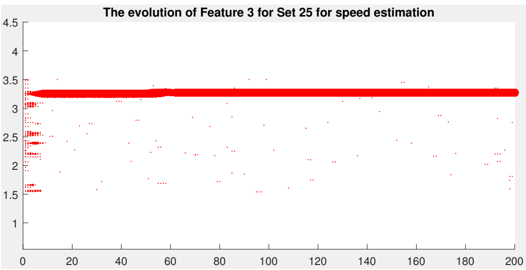

The evolution of Feature 3 for Set 20 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

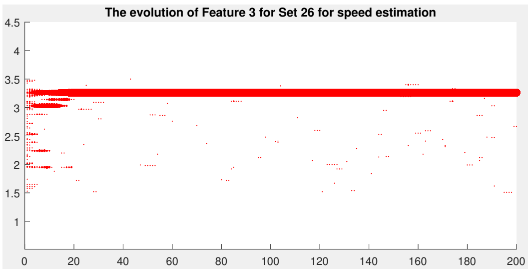

The evolution of Feature 3 for Set 21 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

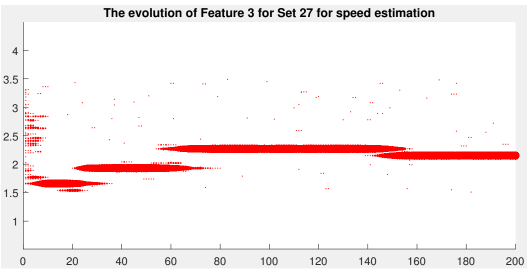

The evolution of Feature 3 for Set 22 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200


The evolution of Feature 3 for Set 23 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
20
40
60
80
100
120
140
160
180
200

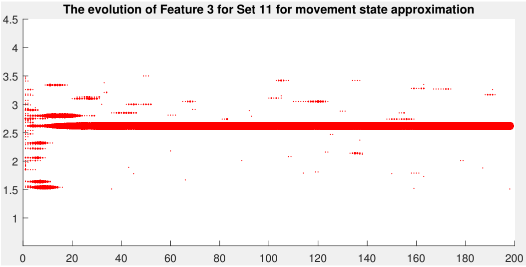

The evolution of Feature 3 for Set 24 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

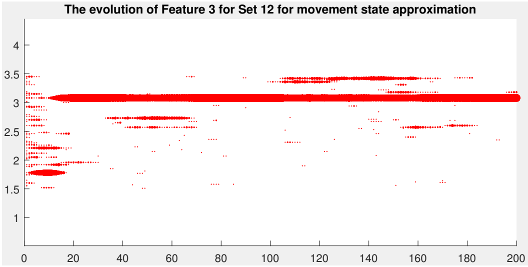

The evolution of Feature 3 for Set 25 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

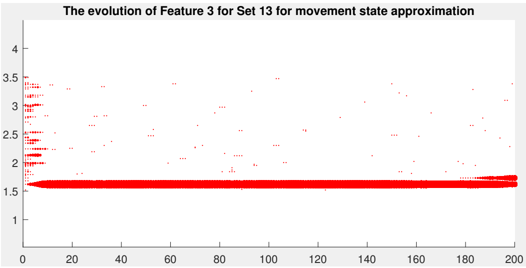

The evolution of Feature 3 for Set 26 for speed estimation
4.5
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

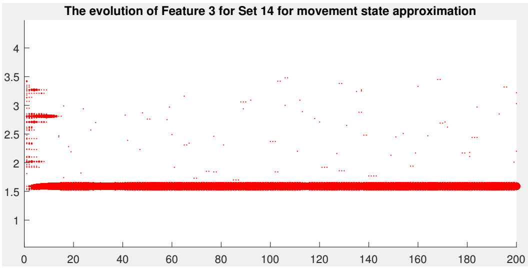

The evolution of Feature 3 for Set 27 for speed estimation
4
3.5
3
2.5
2
1.5
1
0
20
40
60
80
100
120
140
160
180
200

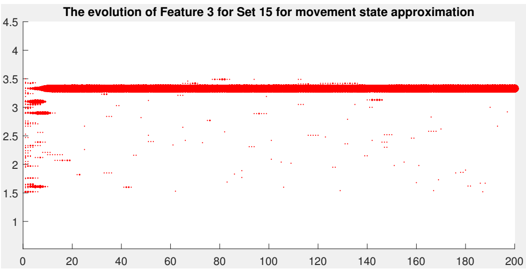
F.4 The Evolution of the Spike Size Gene for All Sets for Movement State Approximation

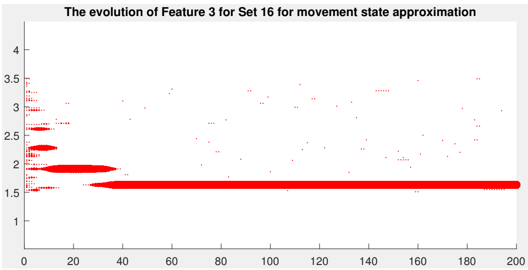


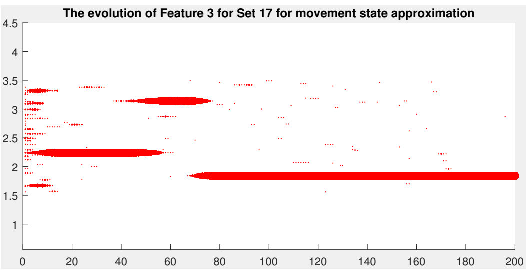


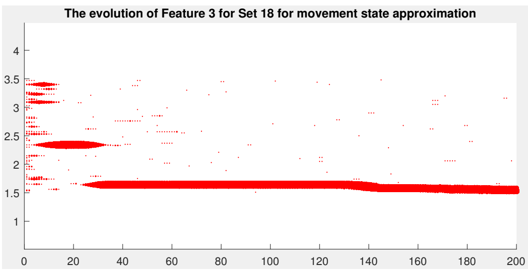


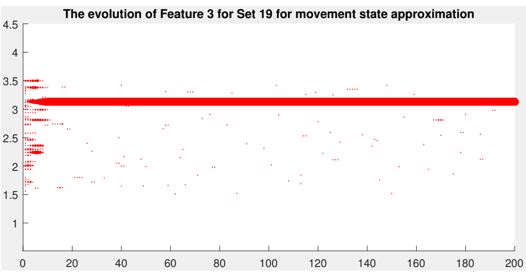


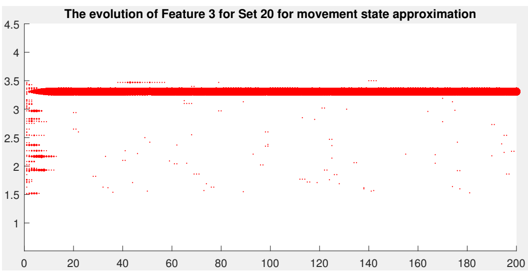


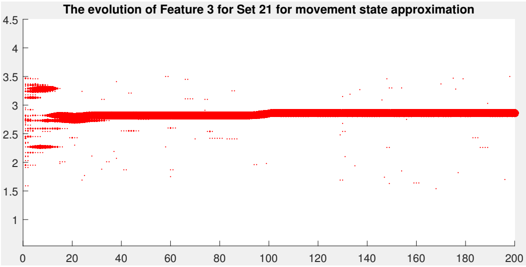


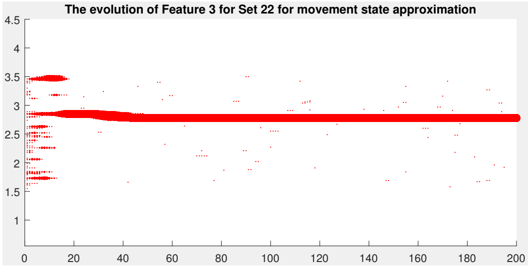


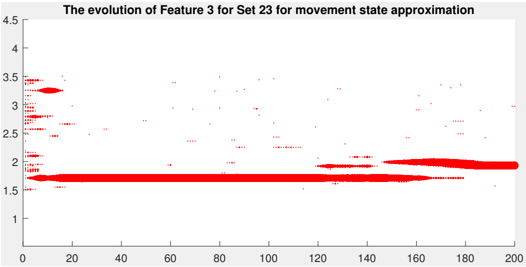


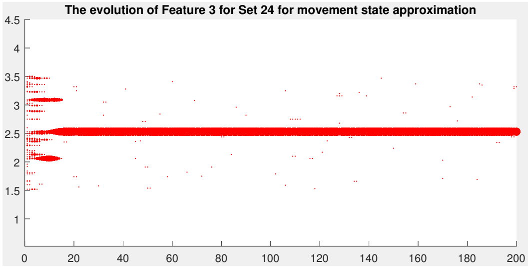


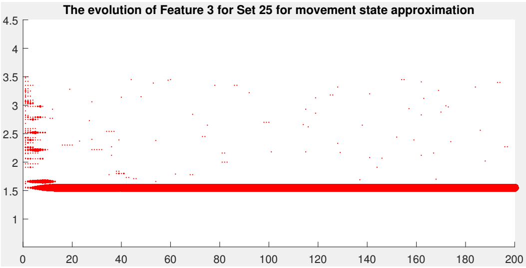


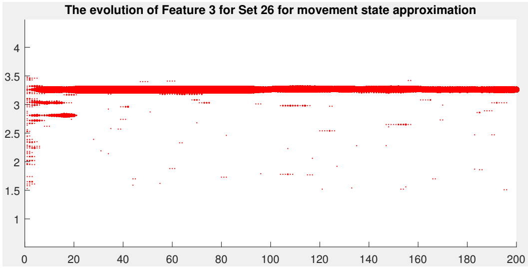


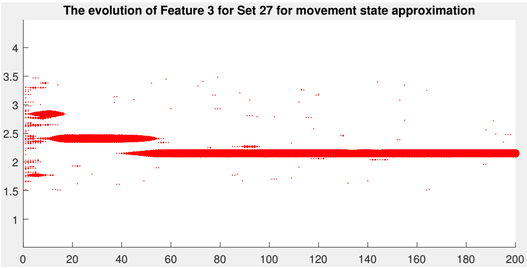




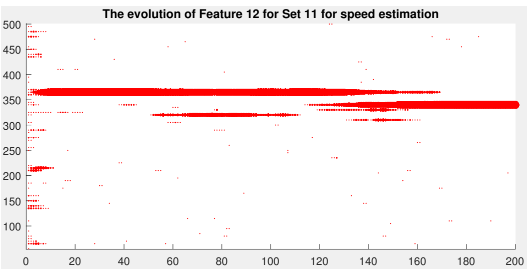


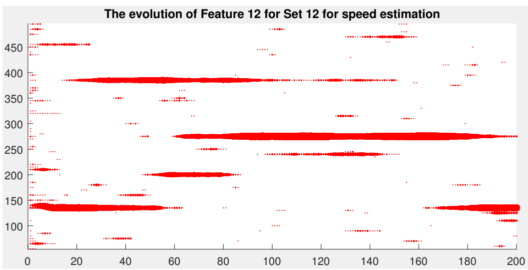


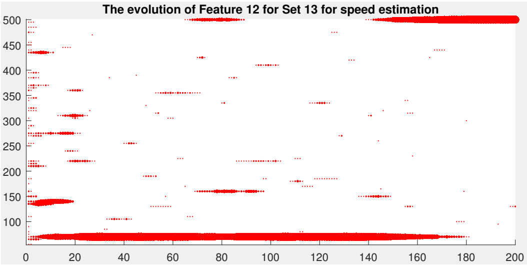


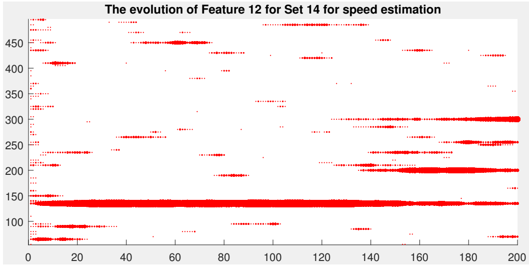


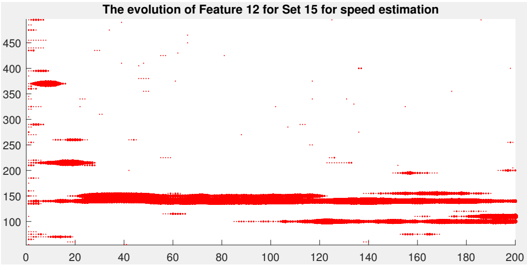
F.5 The Evolution of the Minimum Pressure Gene for All Sets for Speed Estimation

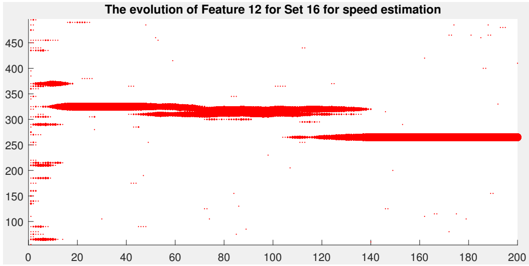


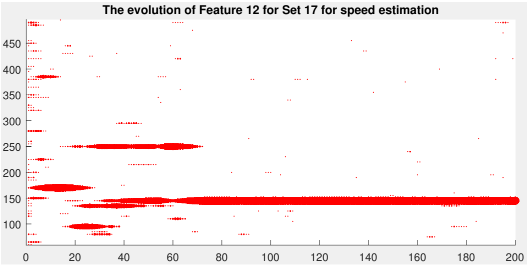


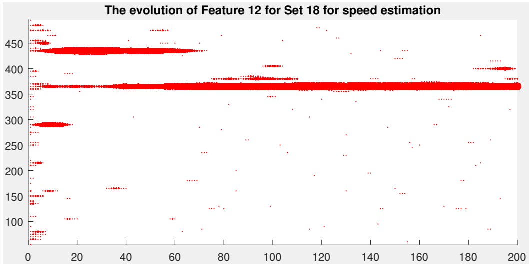

The evolution of Feature 12 for Set 13 for speed estimation

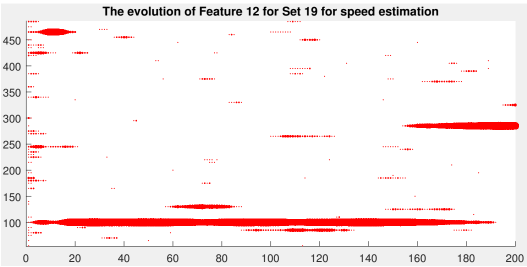

The evolution of Feature 12 for Set 14 for speed estimation

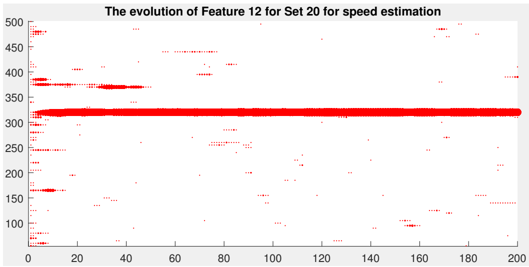

The evolution of Feature 12 for Set 15 for speed estimation

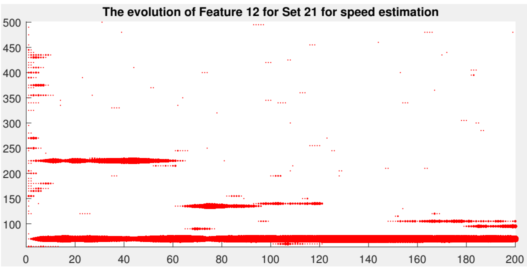

The evolution of Feature 12 for Set 16 for speed estimation

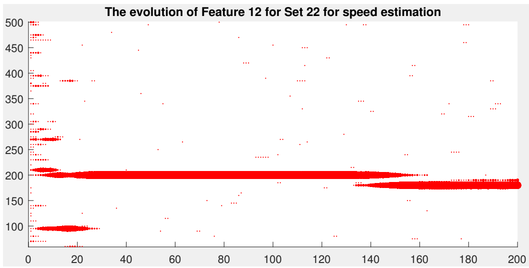

The evolution of Feature 12 for Set 17 for speed estimation

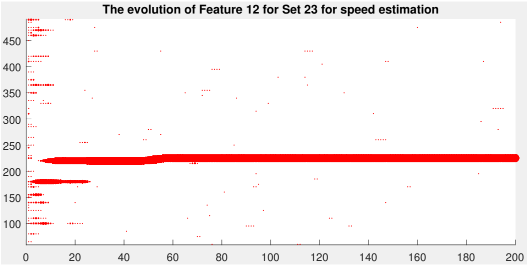

The evolution of Feature 12 for Set 18 for speed estimation

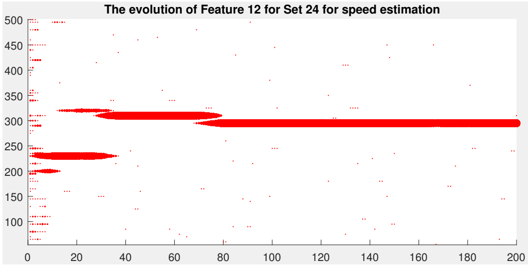

The evolution of Feature 12 for Set 19 for speed estimation

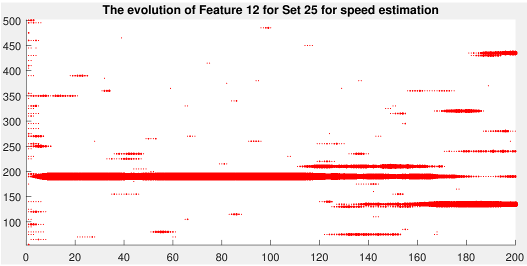

The evolution of Feature 12 for Set 20 for speed estimation

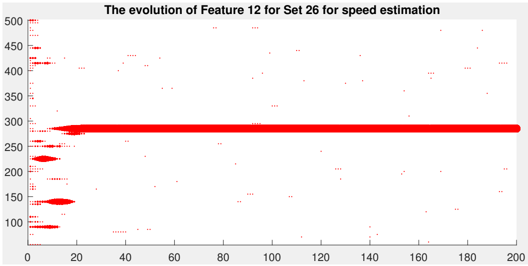

The evolution of Feature 12 for Set 21 for speed estimation

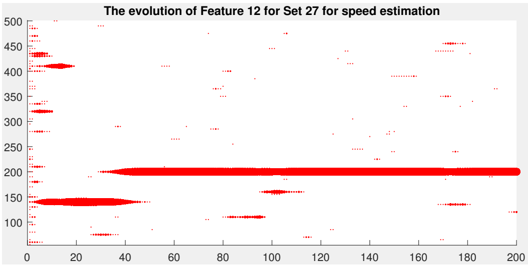

The evolution of Feature 12 for Set 22 for speed estimation



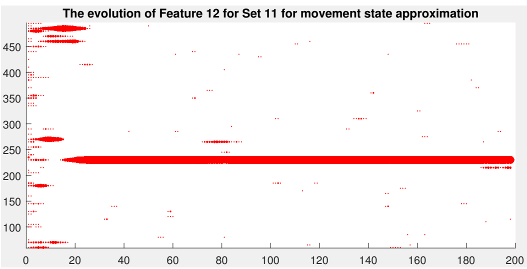


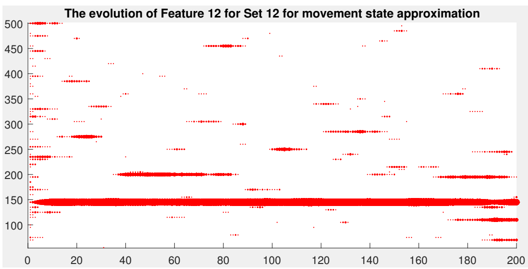


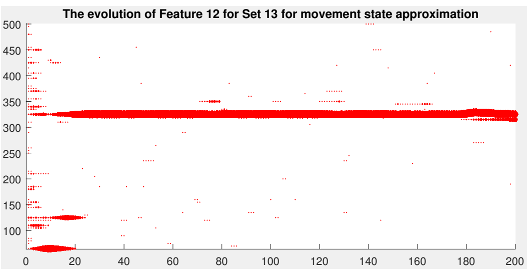


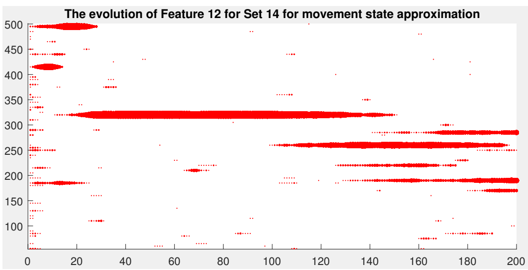


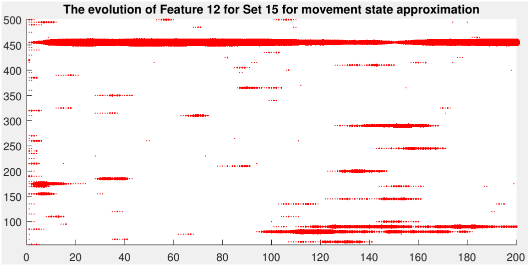
F.6 The Evolution of the Upper Pressure Limit Gene on Pressure Sensor One for All Sets for Speed Estimation

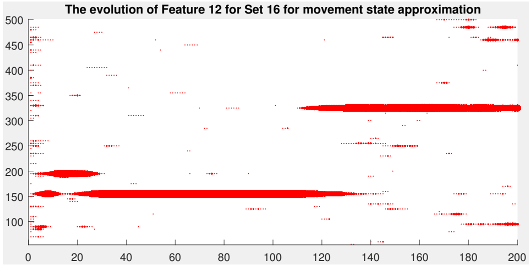


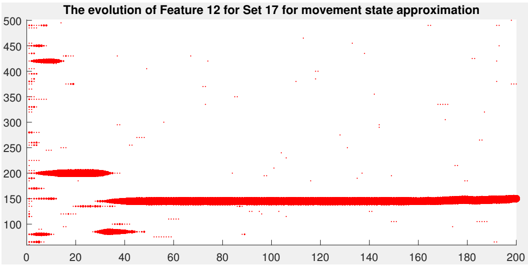


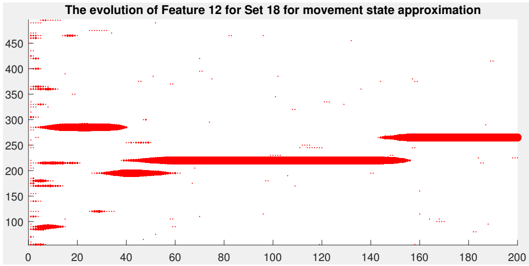


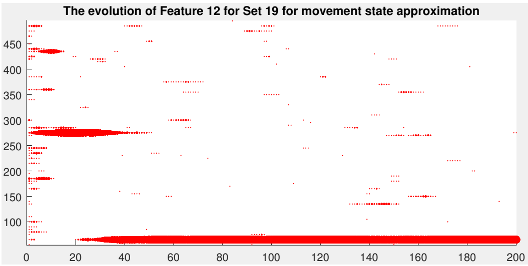


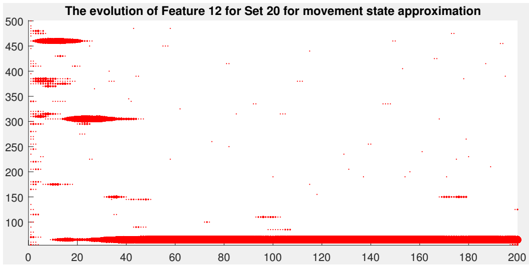

The evolution of Feature 12 for Set 15 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

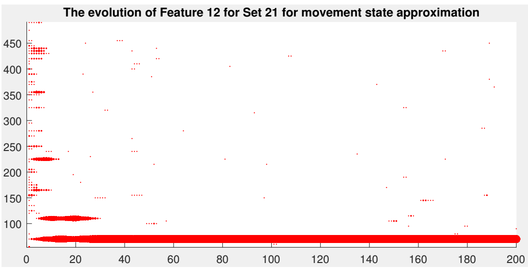

The evolution of Feature 12 for Set 16 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

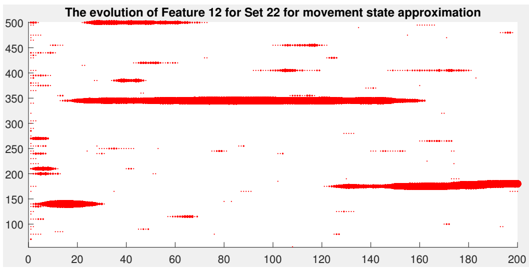

The evolution of Feature 12 for Set 17 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

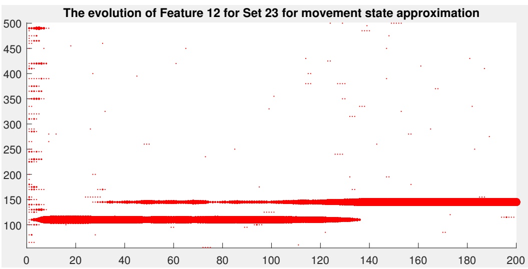

The evolution of Feature 12 for Set 18 for movement state approximation
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

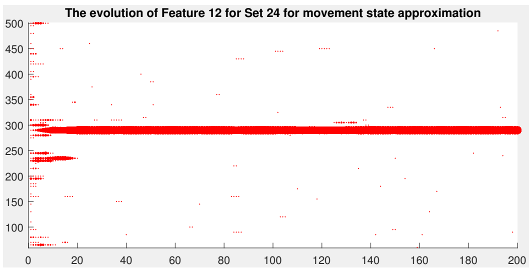

The evolution of Feature 12 for Set 19 for movement state approximation
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

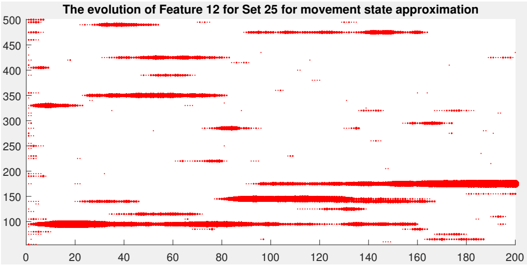

The evolution of Feature 12 for Set 20 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

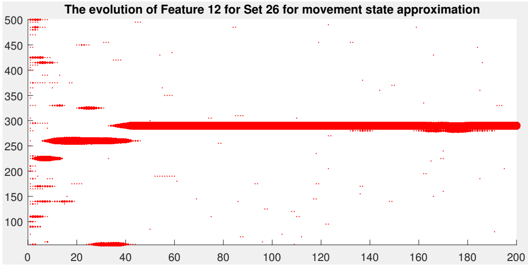

The evolution of Feature 12 for Set 21 for movement state approximation
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

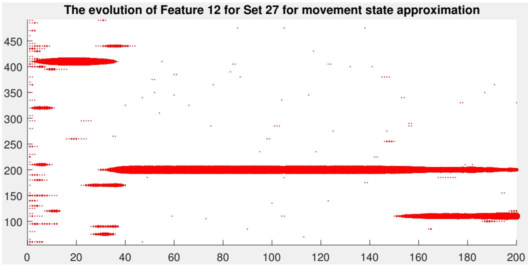

The evolution of Feature 12 for Set 22 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 12 for Set 23 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

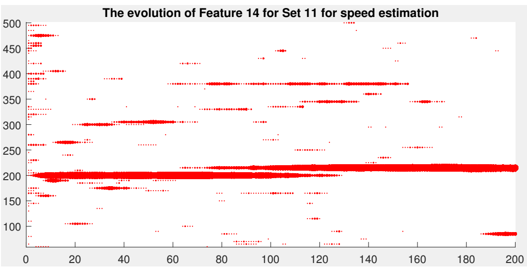

The evolution of Feature 12 for Set 24 for movement state approximation
500
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 200

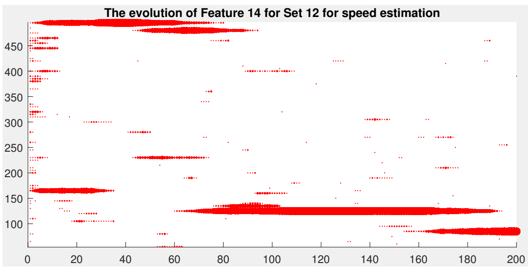


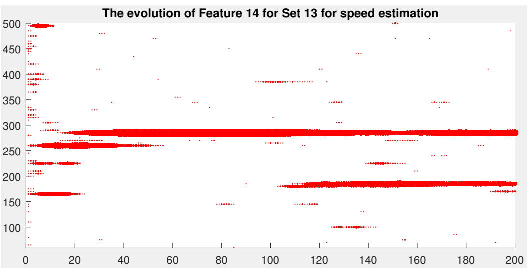


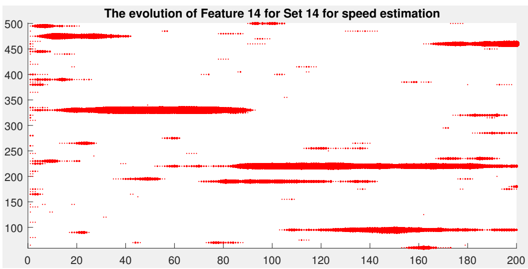


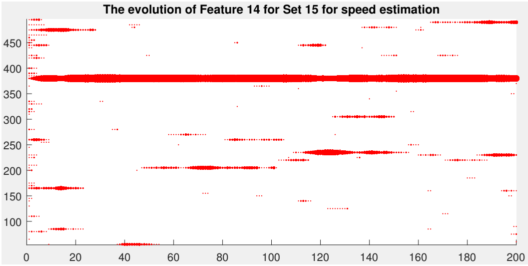
F.7 The Evolution of the Upper Pressure Limit Gene on Pressure Sensor One for All Sets for Movement State Approximation

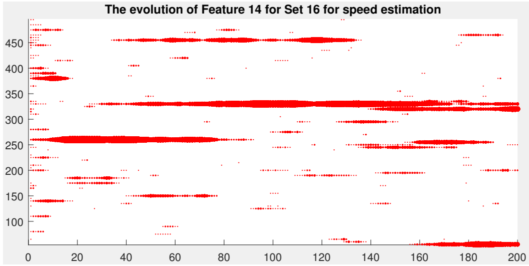


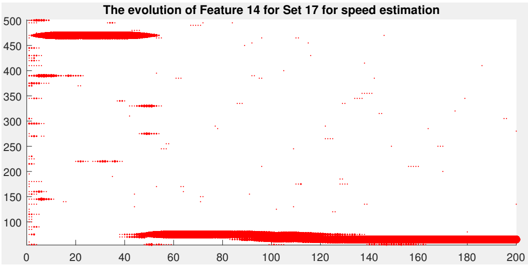


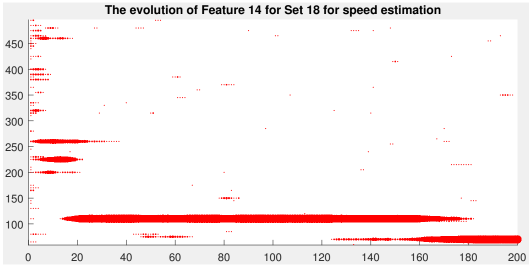


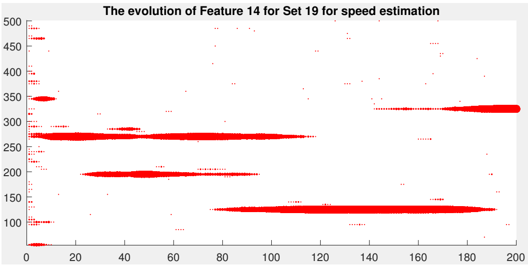


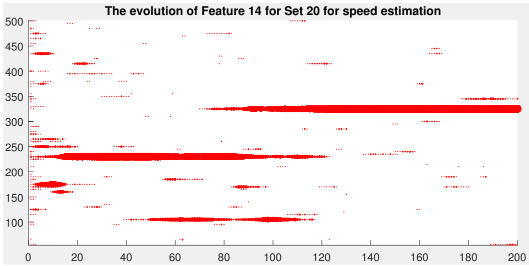

The evolution of Feature 14 for Set 15 for speed estimation

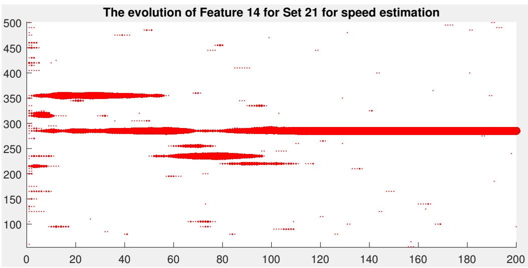

The evolution of Feature 14 for Set 16 for speed estimation

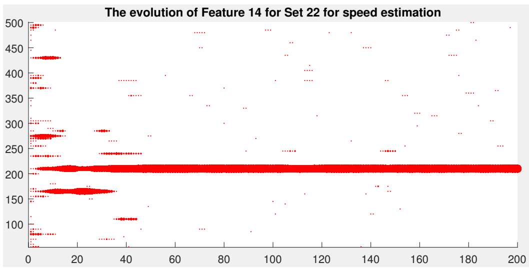

The evolution of Feature 14 for Set 17 for speed estimation

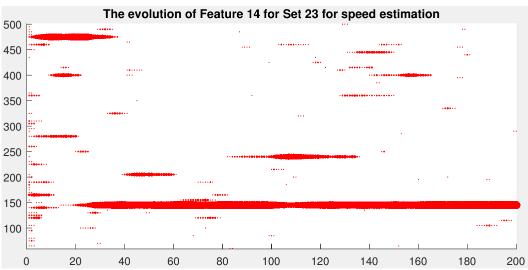

The evolution of Feature 14 for Set 18 for speed estimation

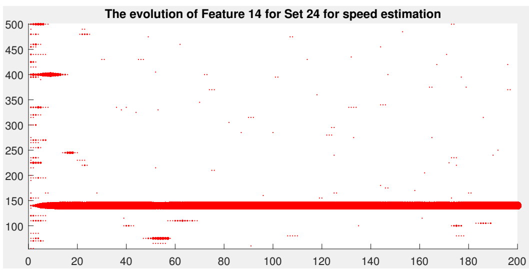

The evolution of Feature 14 for Set 19 for speed estimation

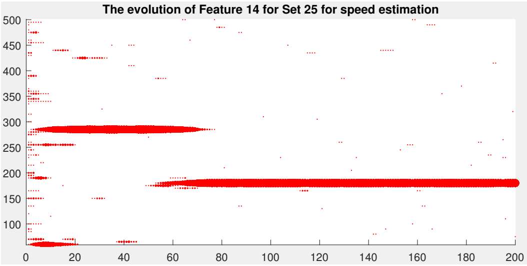

The evolution of Feature 14 for Set 20 for speed estimation

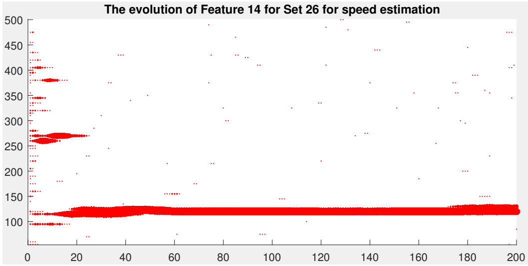

The evolution of Feature 14 for Set 21 for speed estimation

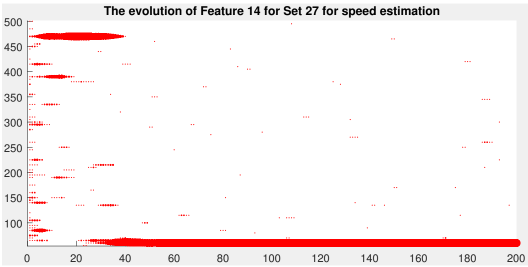

The evolution of Feature 14 for Set 22 for speed estimation


The evolution of Feature 14 for Set 23 for speed estimation

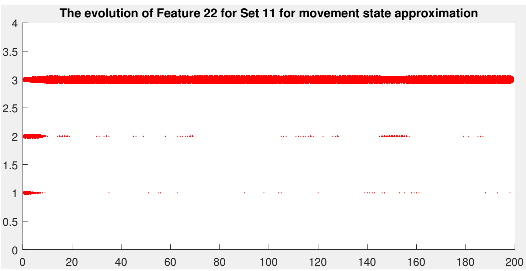

The evolution of Feature 14 for Set 24 for speed estimation

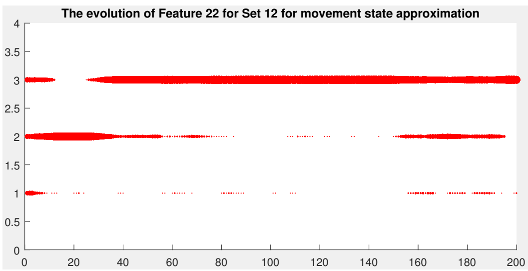


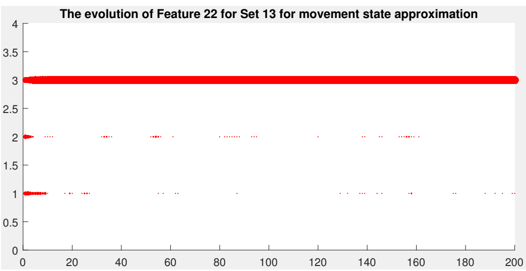


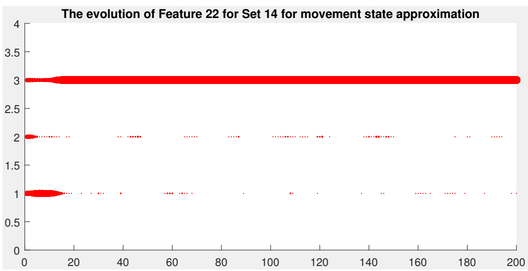


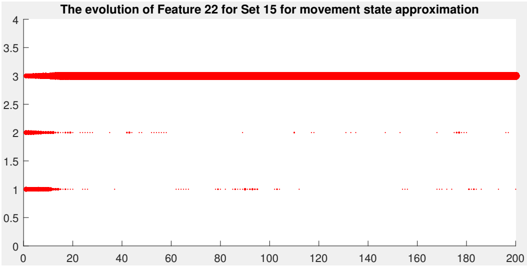
F.8 The Evolution of the Gene Determining the Optimal Number of Layers to Be Used in the Artificial Neural Network for All Data Sets for Movement State Approximation

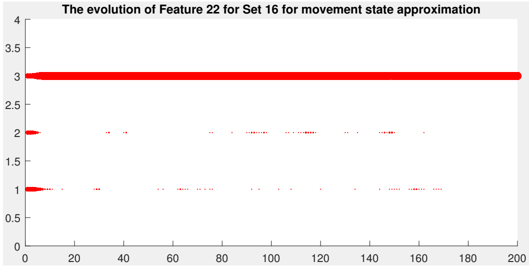


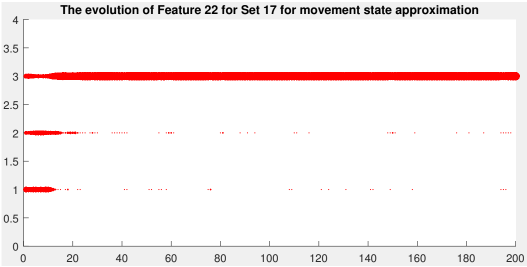


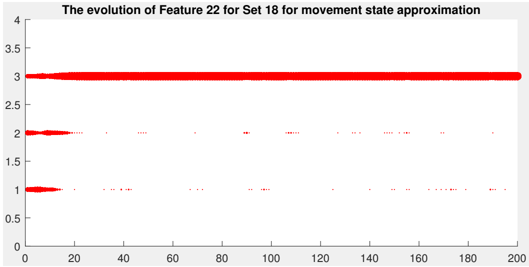


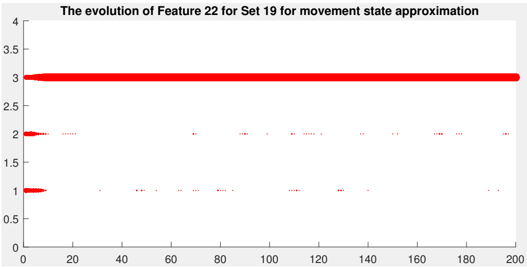


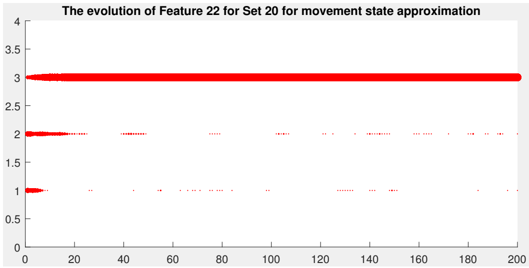

The evolution of Feature 22 for Set 15 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

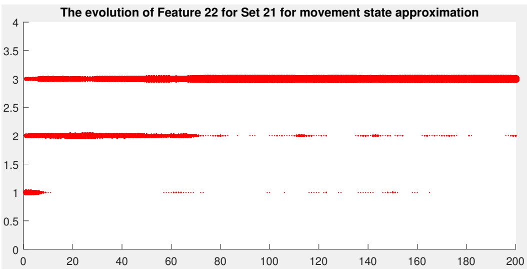

The evolution of Feature 22 for Set 16 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

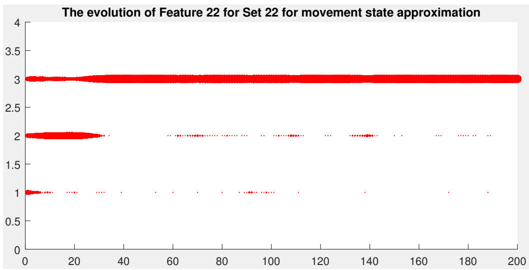

The evolution of Feature 22 for Set 17 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

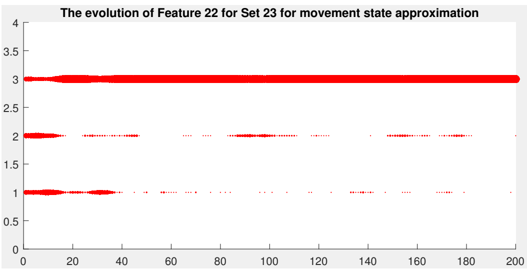

The evolution of Feature 22 for Set 18 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

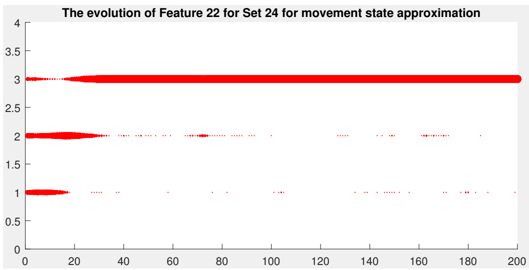

The evolution of Feature 22 for Set 19 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

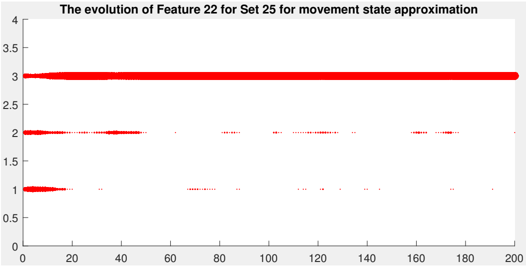

The evolution of Feature 22 for Set 20 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

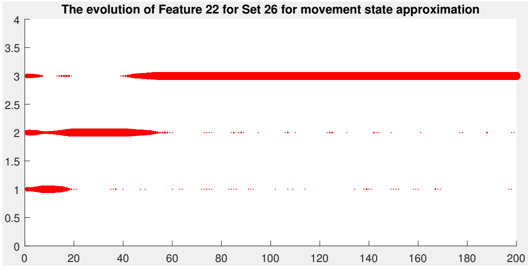

The evolution of Feature 22 for Set 21 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200

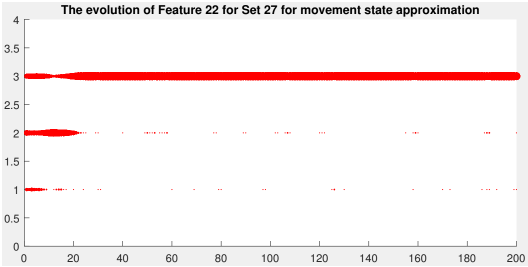

The evolution of Feature 22 for Set 22 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 22 for Set 23 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 22 for Set 24 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0 20 40 60 80 100 120 140 160 180 200


The evolution of Feature 22 for Set 25 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0
20
40
60
80
100
120
140
160
180
200


The evolution of Feature 22 for Set 26 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0
20
40
60
80
100
120
140
160
180
200

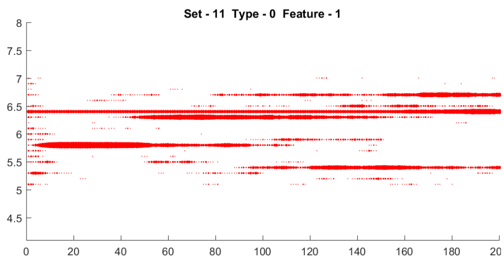

The evolution of Feature 22 for Set 27 for movement state approximation
0
0.5
1
1.5
2
2.5
3
3.5
4
0
20
40
60
80
100
120
140
160
180
200

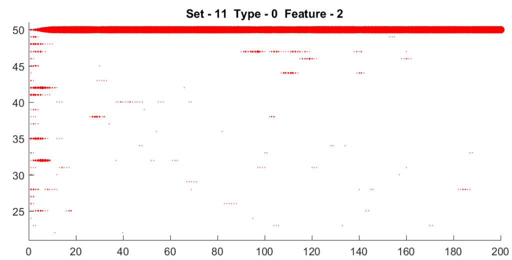
Appendix G

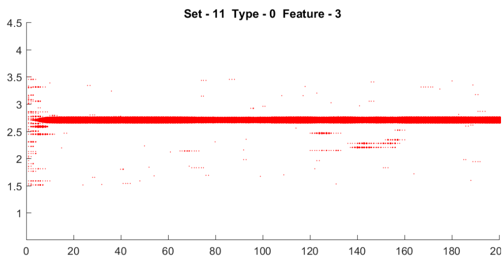
The Evolution of All the Genes for One Set of Data

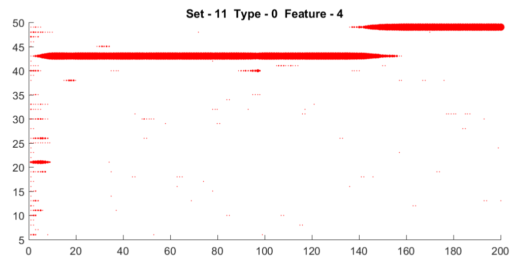
The following diagrams show the evolution of every gene for one set of data.

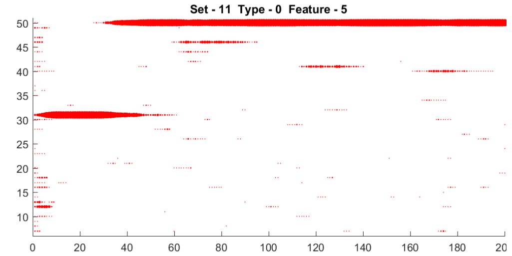
G.1 Data Set 11 - Speed Estimation







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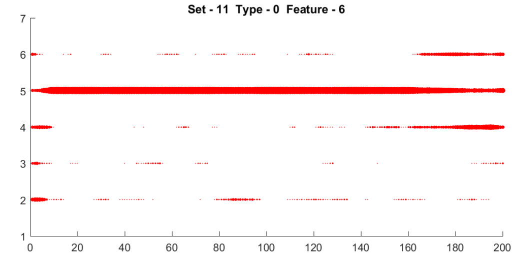
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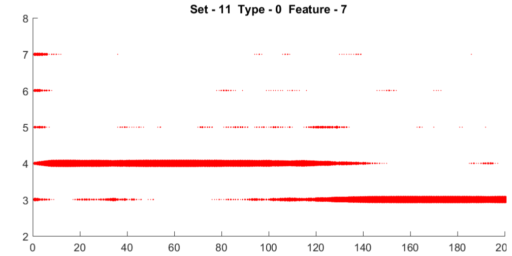
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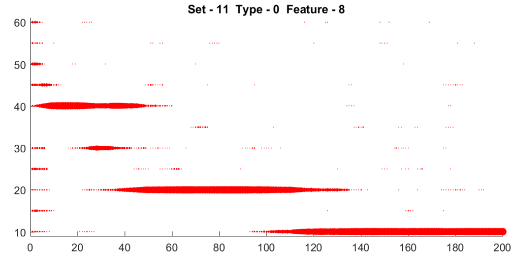
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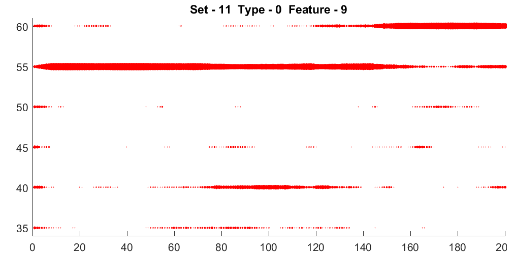
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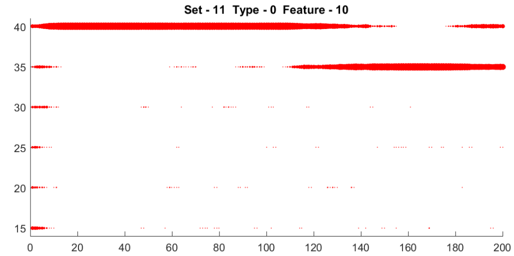
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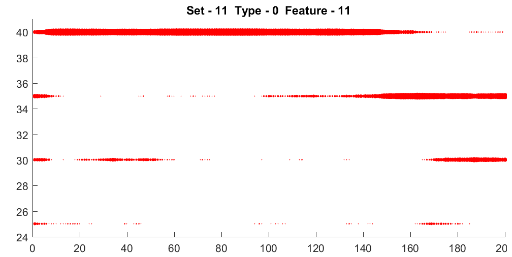
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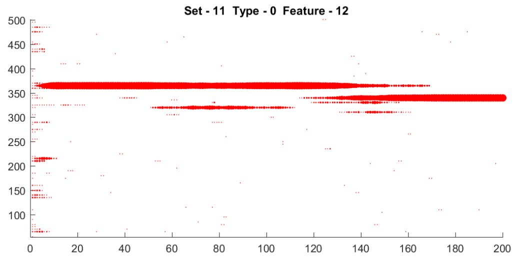
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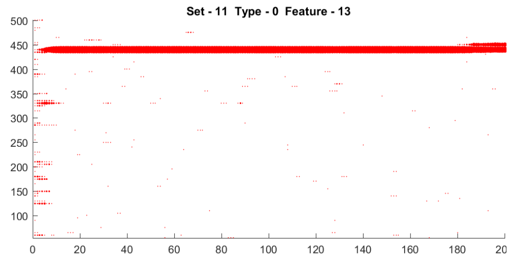
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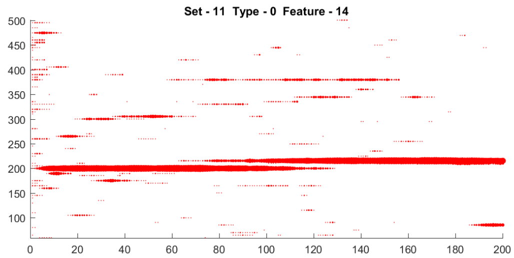
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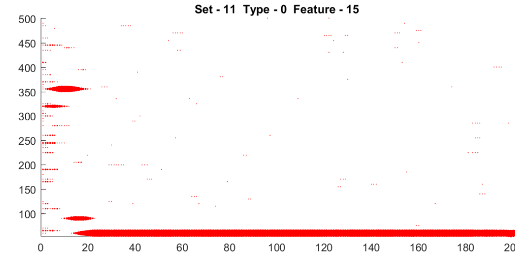
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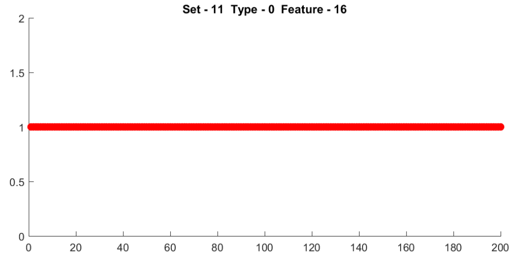
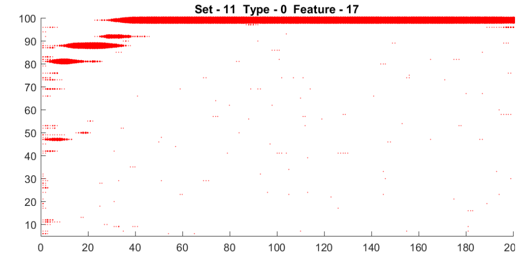
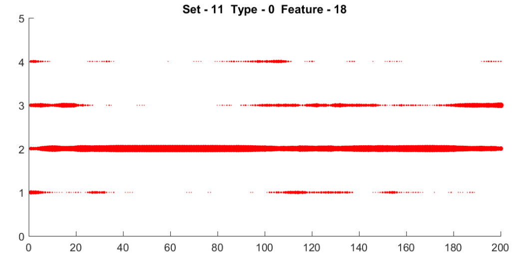
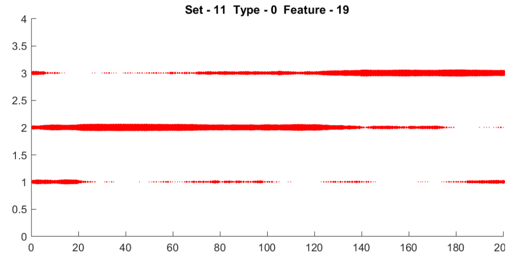
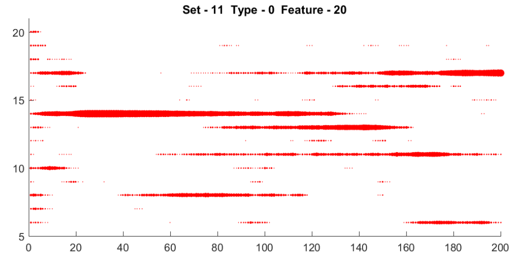
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180 20

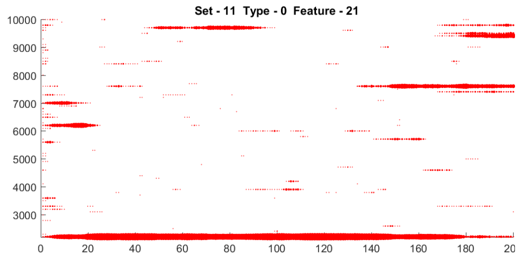

Set - 11 Type - 0 Feature - 16
2
1.5
1
0.5
0
0 20 40 60 80 100 120 140 160 180 200

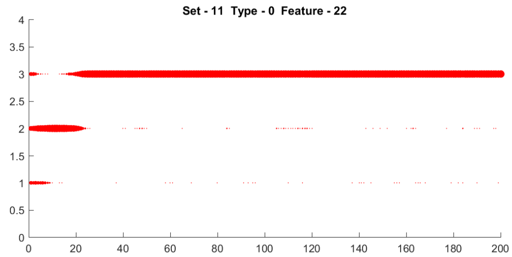

Set - 11 Type - 0 Feature - 17
100
90
80
70
60
50
40
30
20
10
0 20 40 60 80 100 120 140 160 180 20

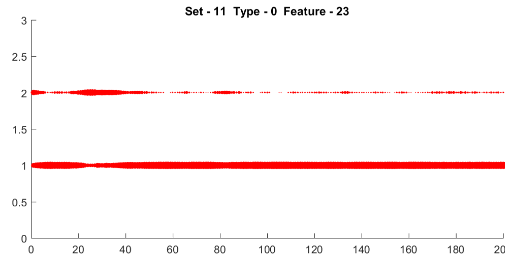

Set - 11 Type - 0 Feature - 18
5
4
3
2
1
0
0 20 40 60 80 100 120 140 160 180 200

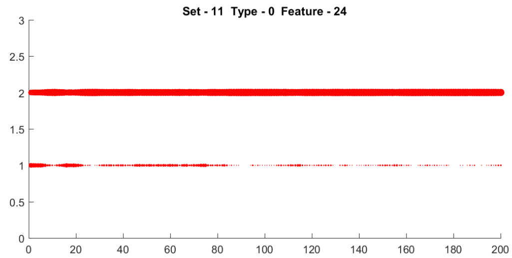

Set - 11 Type - 0 Feature - 19
4
3.5
3
2.5
2
1.5
1
0.5
0
0 20 40 60 80 100 120 140 160 180 20

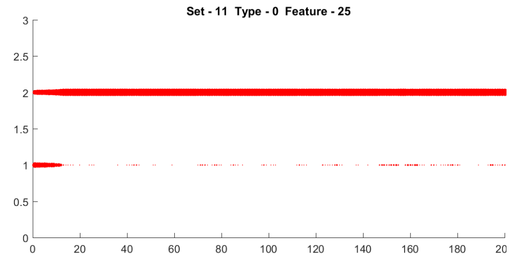

Set - 11 Type - 0 Feature - 20
20
15
10
5
0 20 40 60 80 100 120 140 160 180 200

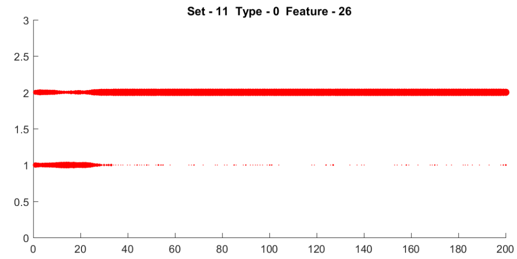

Set - 11 Type - 0 Feature - 21
10000
9000
8000
7000
6000
5000
4000
3000
0 20 40 60 80 100 120 140 160 180 20

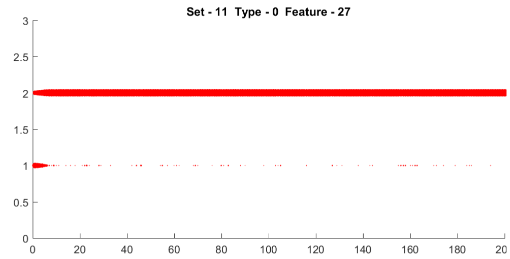

Set - 11 Type - 0 Feature - 22
4
3.5
3
2.5
2
1.5
1
0.5
0
0 20 40 60 80 100 120 140 160 180 200

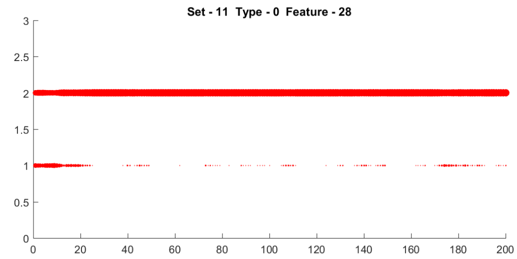

Set - 11 Type - 0 Feature - 23
3
2.5
2
1.5
1
0.5
0
0 20 40 60 80 100 120 140 160 180 20

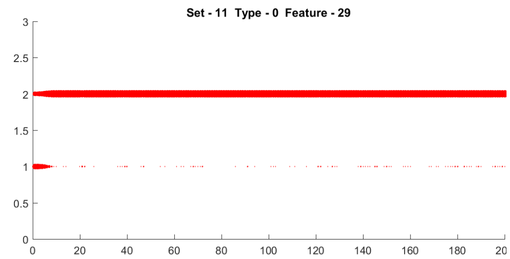

Set - 11 Type - 0 Feature - 24
3
2.5
2
1.5
1
0.5
0
0 20 40 60 80 100 120 140 160 180 200

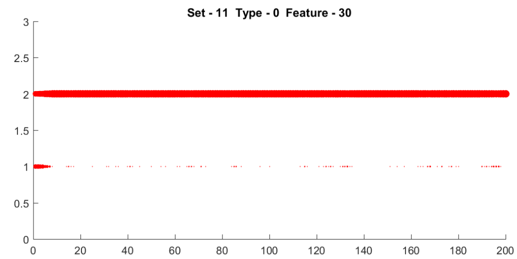


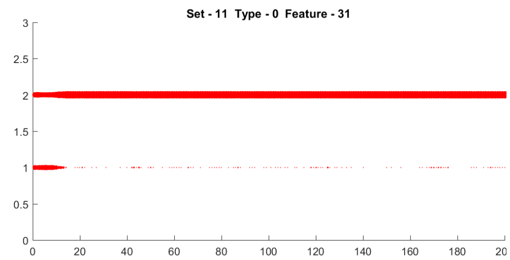


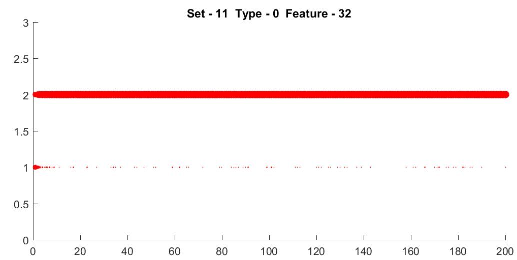




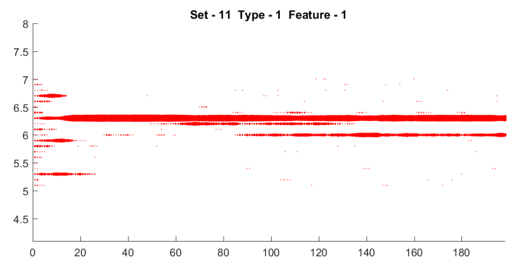


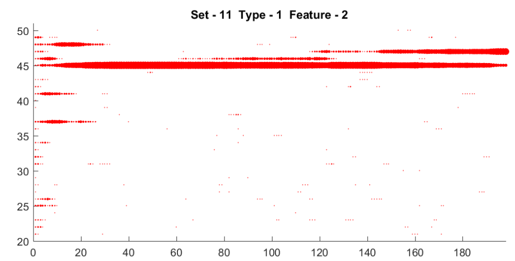


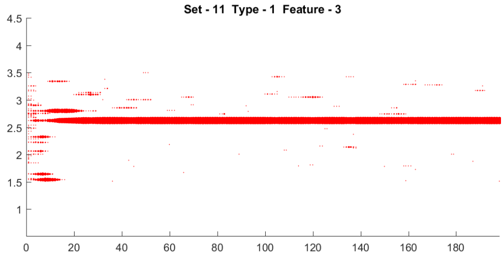


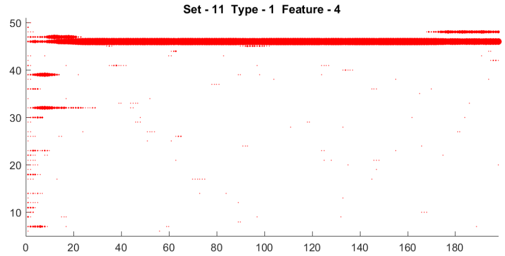


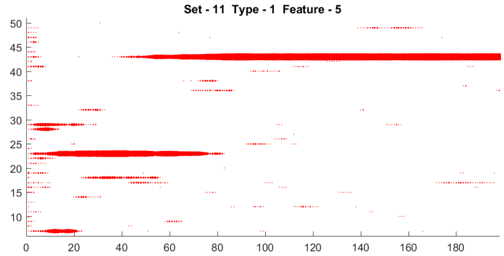
G.2 Data Set 11 - Movement State Approximation

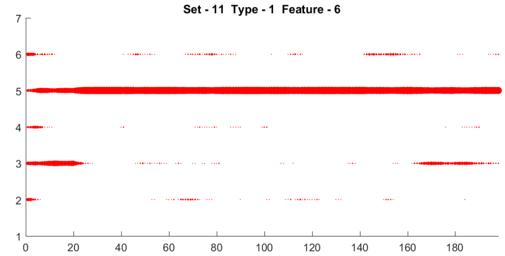


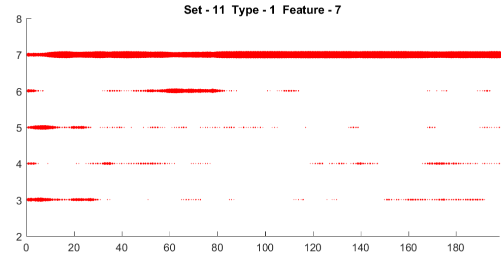


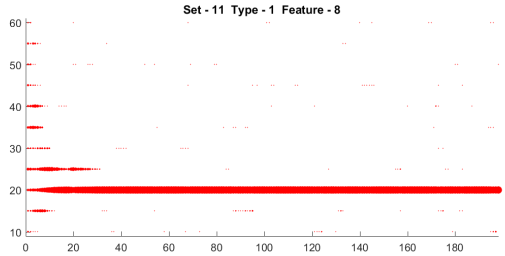

Set - 11 Type - 1 Feature - 3
4.5
4
3.5
3
2.5
2
1.5
1
0 20 40 60 80 100 120 140 160 180

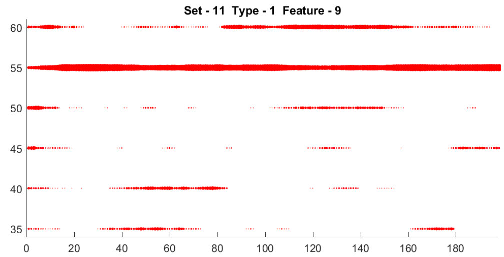

Set - 11 Type - 1 Feature - 4
50
40
30
20
10
0 20 40 60 80 100 120 140 160 180

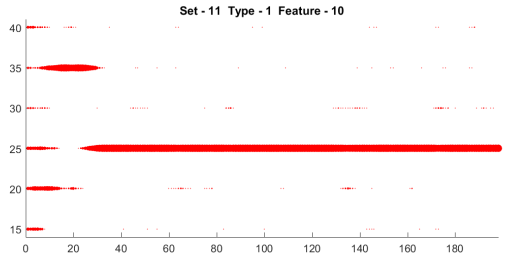

Set - 11 Type - 1 Feature - 5
50
45
40
35
30
25
20
15
10
0 20 40 60 80 100 120 140 160 180

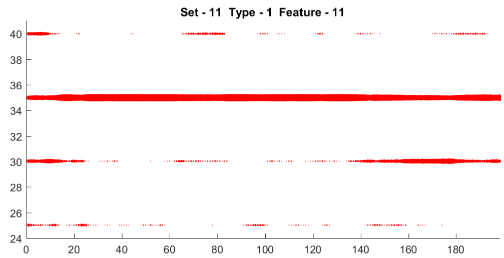

Set - 11 Type - 1 Feature - 6
7
6
5
4
3
2
1
0 20 40 60 80 100 120 140 160 180

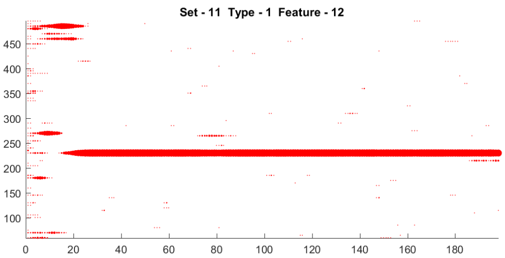

Set - 11 Type - 1 Feature - 7
8
7
6
5
4
3
2
0 20 40 60 80 100 120 140 160 180

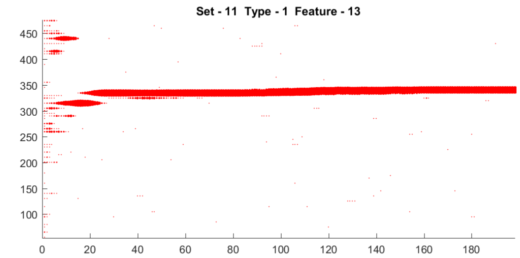

Set - 11 Type - 1 Feature - 8
60
50
40
30
20
10
0 20 40 60 80 100 120 140 160 180

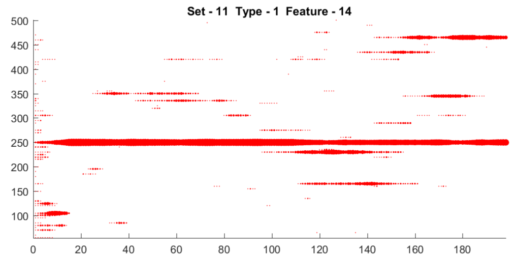

Set - 11 Type - 1 Feature - 9
60
55
50
45
40
35
0 20 40 60 80 100 120 140 160 180

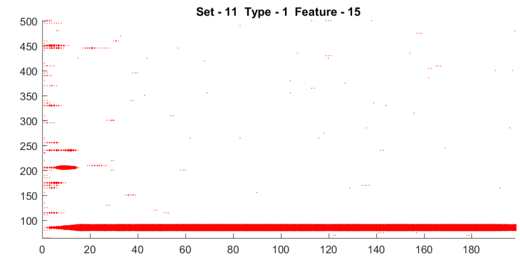

Set - 11 Type - 1 Feature - 10
40
35
30
25
20
15
0 20 40 60 80 100 120 140 160 180

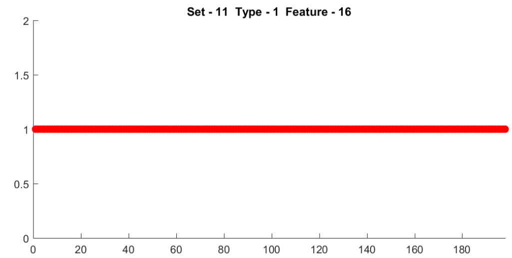

Set - 11 Type - 1 Feature - 11
40
38
36
34
32
30
28
26
24
0 20 40 60 80 100 120 140 160 180

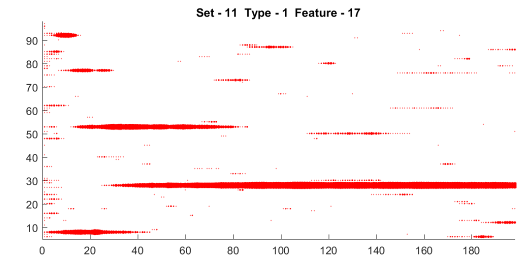

Set - 11 Type - 1 Feature - 12
450
400
350
300
250
200
150
100
0 20 40 60 80 100 120 140 160 180

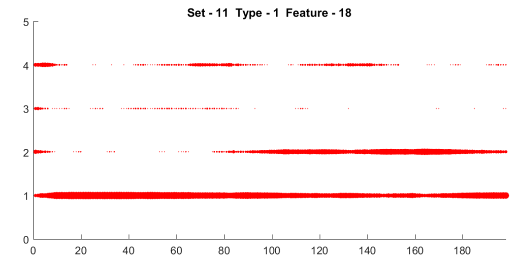

Set - 11 Type - 1 Feature - 13

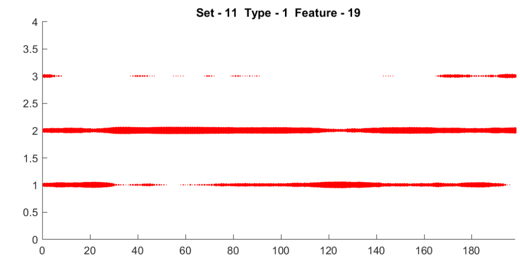

Set - 11 Type - 1 Feature - 14

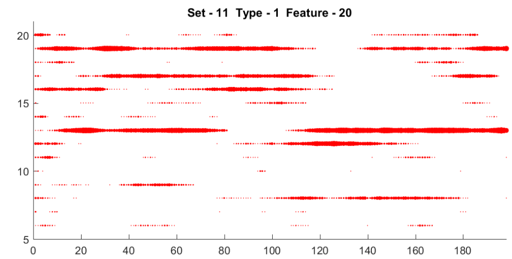

Set - 11 Type - 1 Feature - 15


Set - 11 Type - 1 Feature - 16


Set - 11 Type - 1 Feature - 17


Set - 11 Type - 1 Feature - 18


Set - 11 Type - 1 Feature - 19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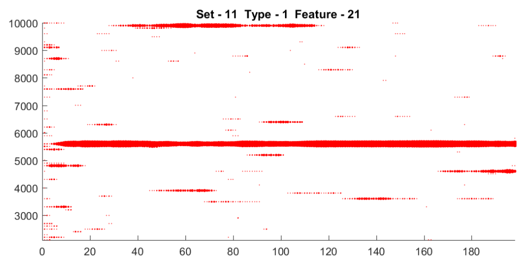
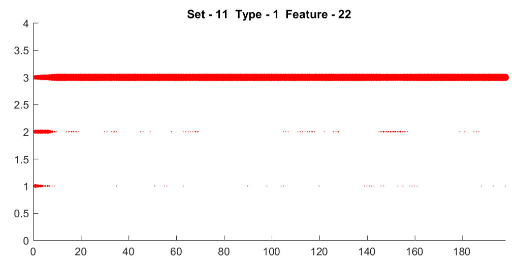

Set - 11 Type - 1 Feature - 21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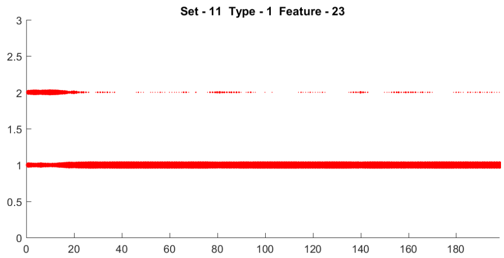
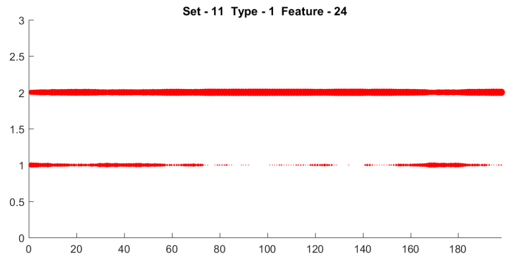
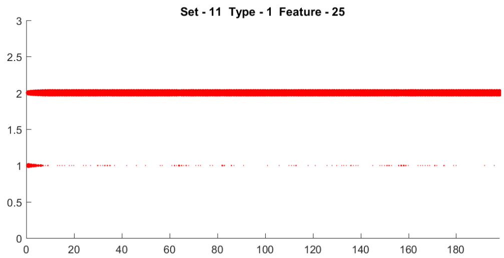
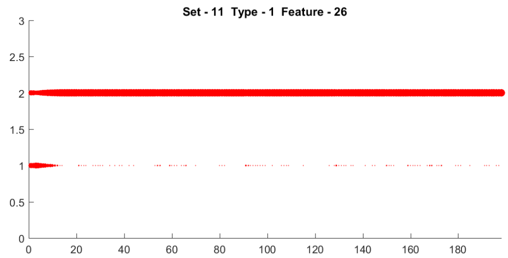
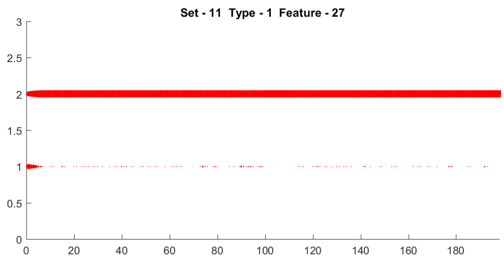
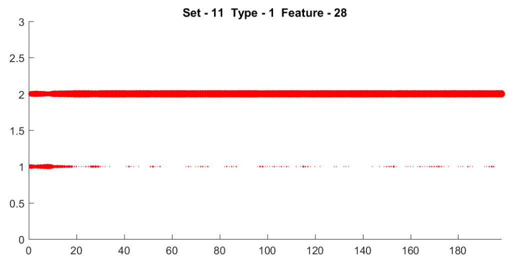

Set - 11 Type - 1 Feature - 23
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180

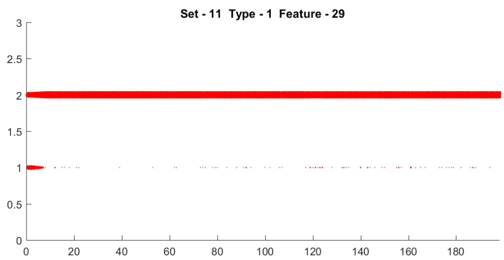

Set - 11 Type - 1 Feature - 24
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180

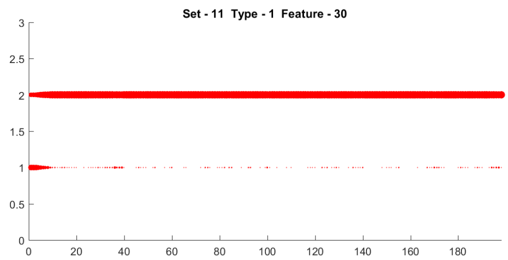

Set - 11 Type - 1 Feature - 25
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180

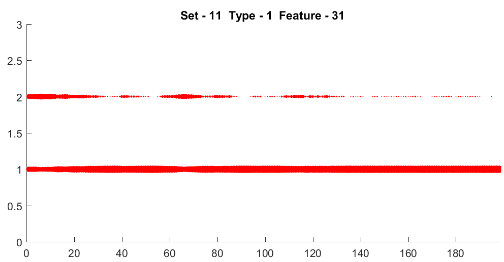

Set - 11 Type - 1 Feature - 26
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180

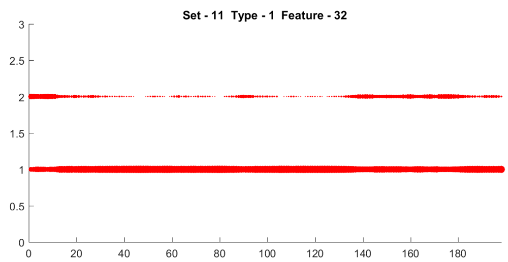

Set - 11 Type - 1 Feature - 27
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180


Set - 11 Type - 1 Feature - 28
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180


Set - 11 Type - 1 Feature - 29
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180


Set - 11 Type - 1 Feature - 30
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180


Set - 11 Type - 1 Feature - 31
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180


Set - 11 Type - 1 Feature - 32
0 0.5 1 1.5 2 2.5 3
0 20 40 60 80 100 120 140 160 180

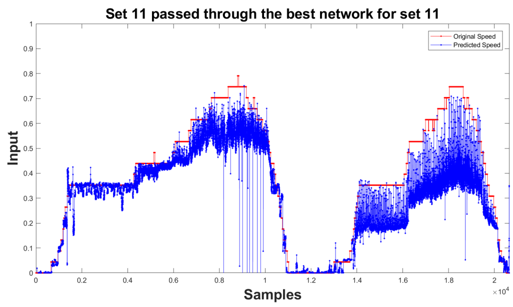
Appendix H

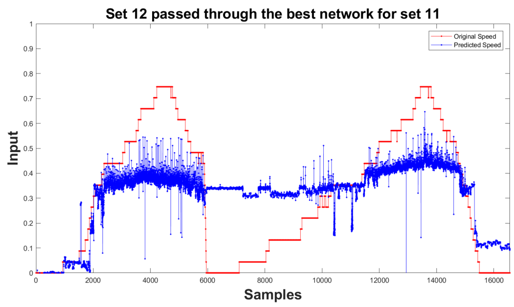
Other Networks

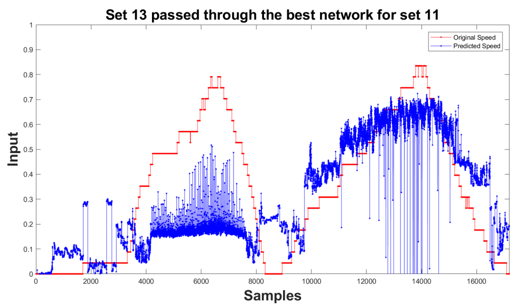
The following diagrams show the result of putting one set of data through the optimal network for another set of data for a sample of the data sets.

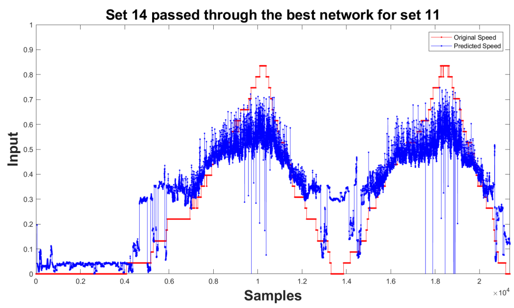
H.1 Speed Estimation

H.1.1 Network 11

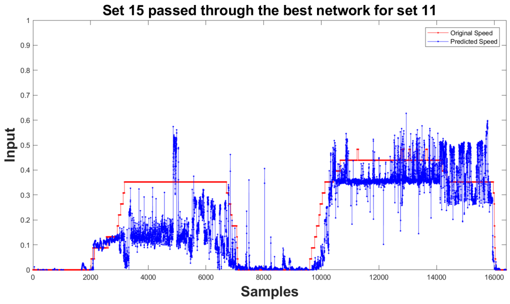




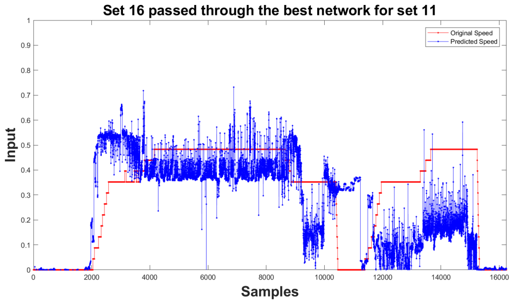




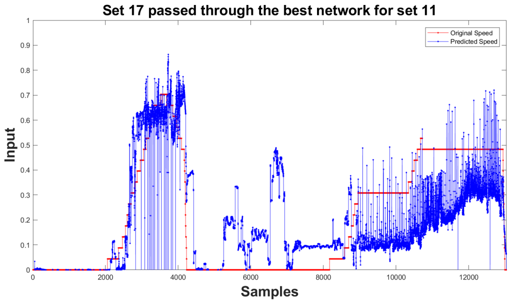
Set 15 passed through the best network for set 11



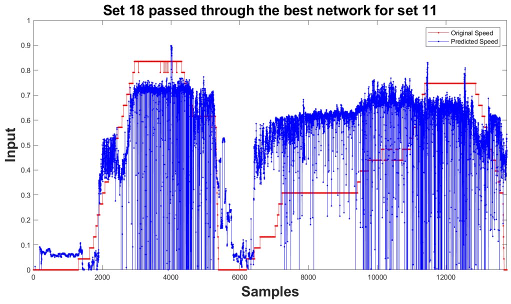
Set 16 passed through the best network for set 11



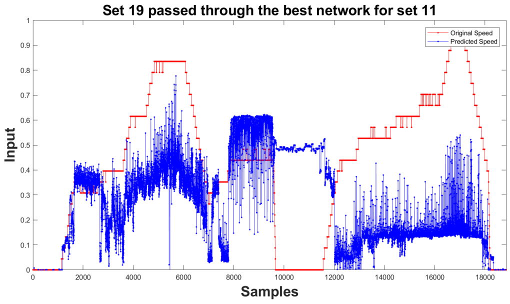
Set 17 passed through the best network for set 11



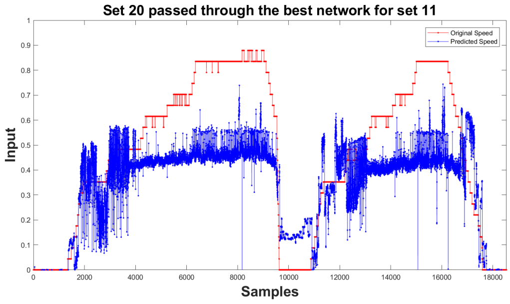
Set 18 passed through the best network for set 11



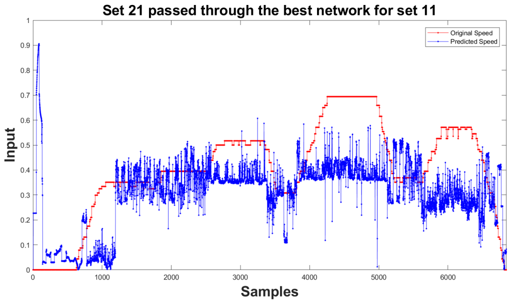
Set 19 passed through the best network for set 11



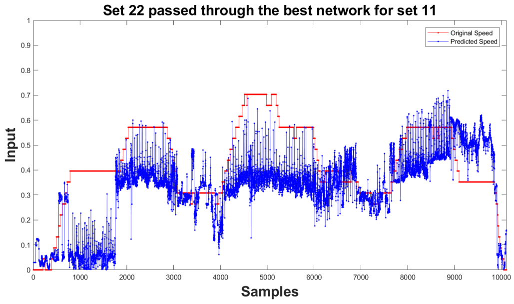
Set 20 passed through the best network for set 11



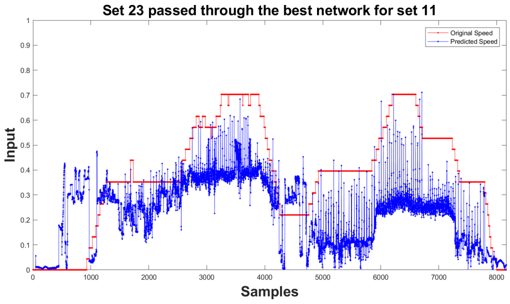
Set 21 passed through the best network for set 11



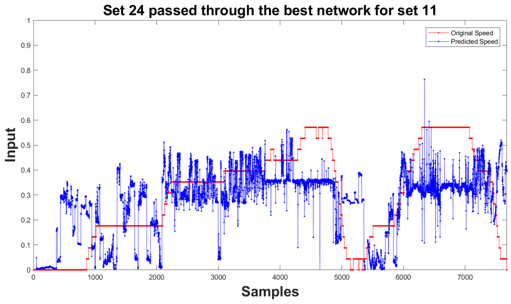
Set 22 passed through the best network for set 11

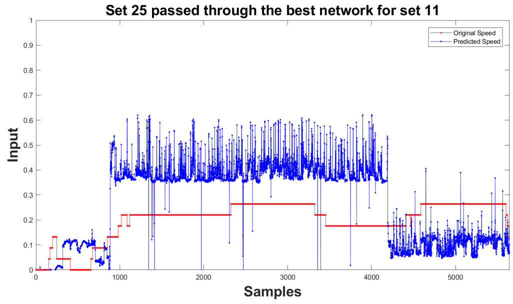


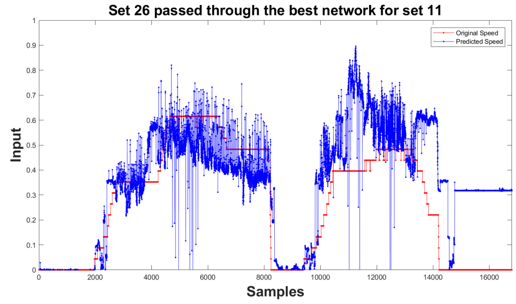
Set 23 passed through the best network for set 11

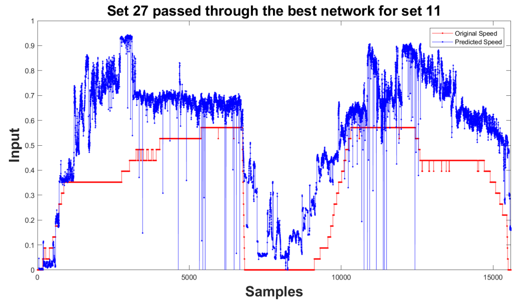


Set 24 passed through the best network for set 11

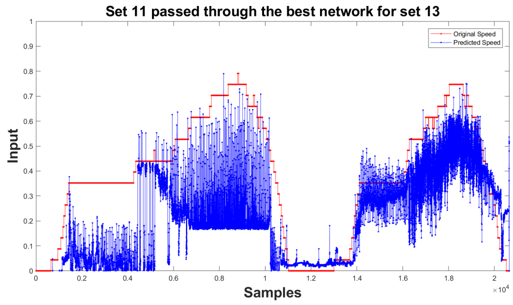


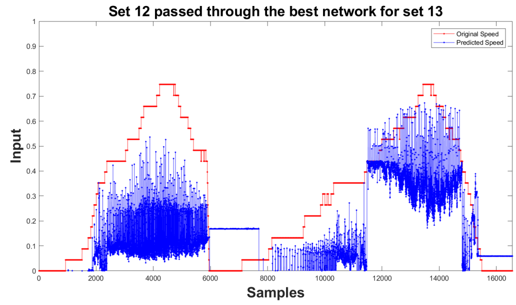


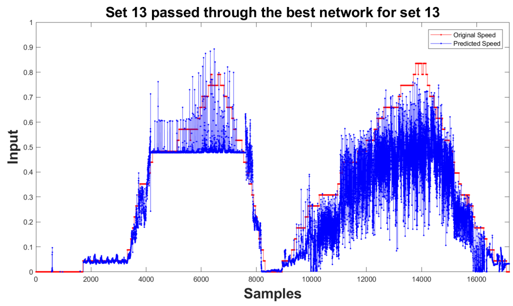


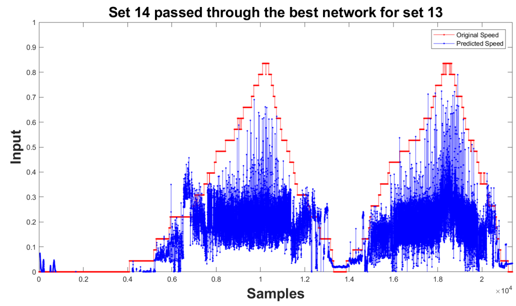


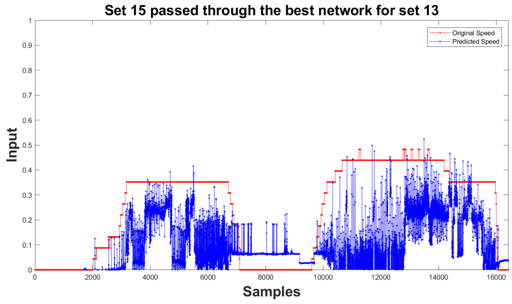
H.1.2 Network 13

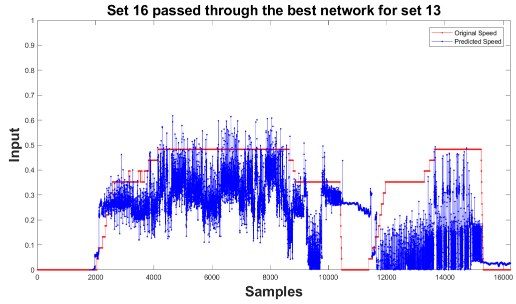


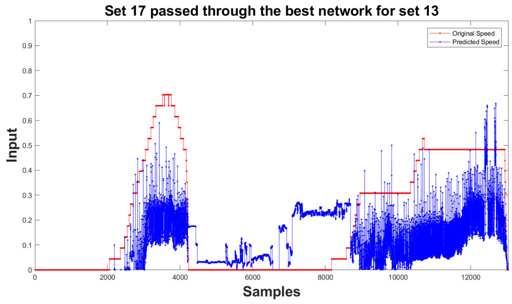


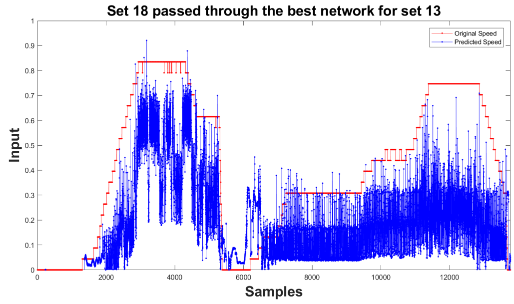


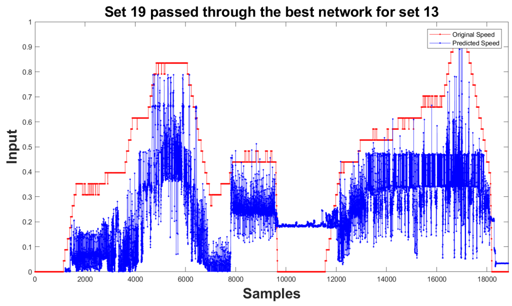


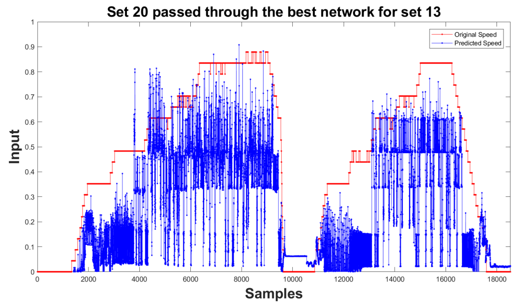

Set 15 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

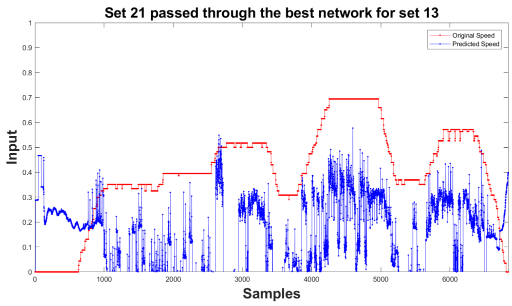

Set 16 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

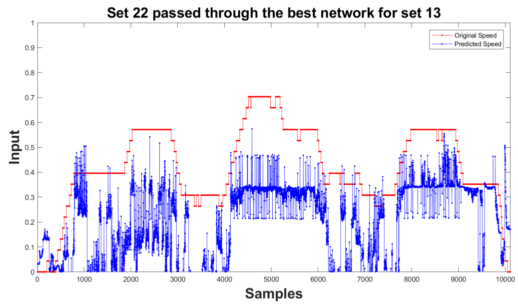

Set 17 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

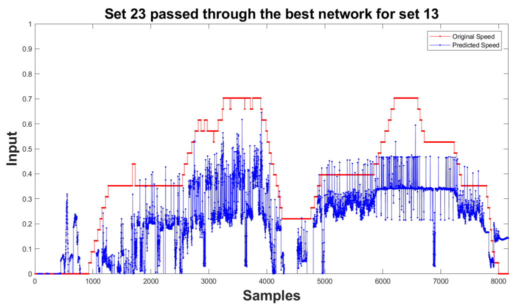

Set 18 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

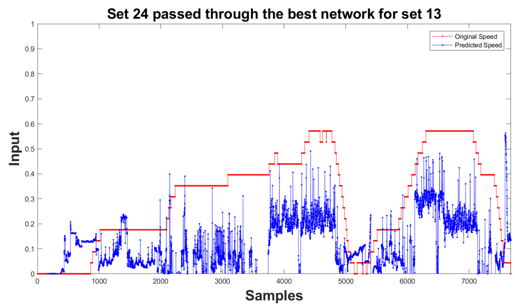

Set 19 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

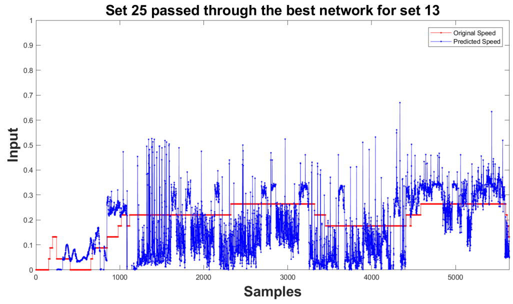

Set 20 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

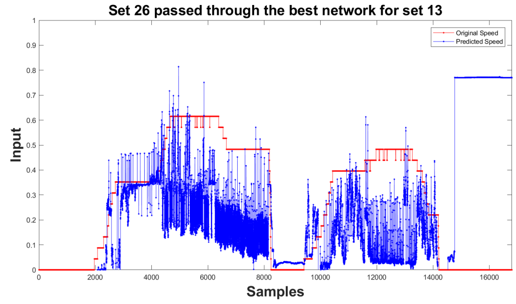

Set 21 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

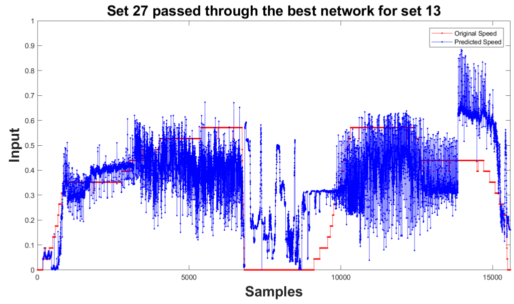

Set 22 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples


Set 23 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

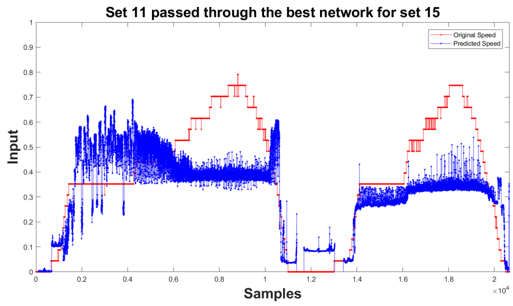

Set 24 passed through the best network for set 13
Original Speed
Predicted Speed
Input
Samples

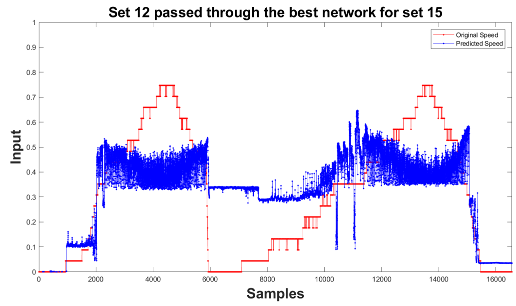


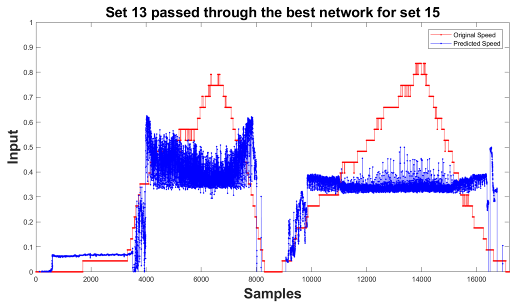


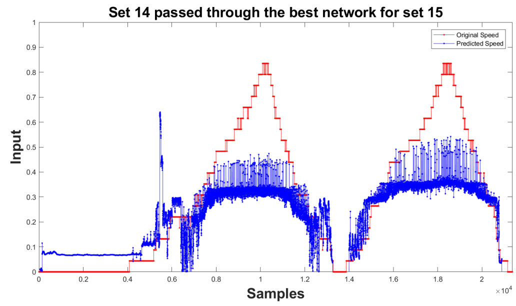


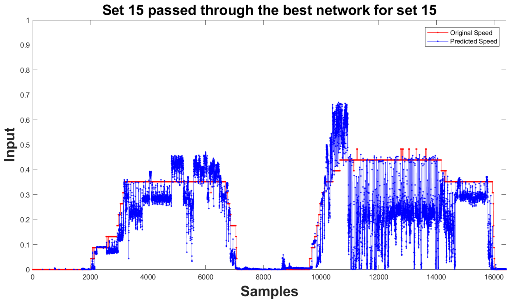
H.1.3 Network 15

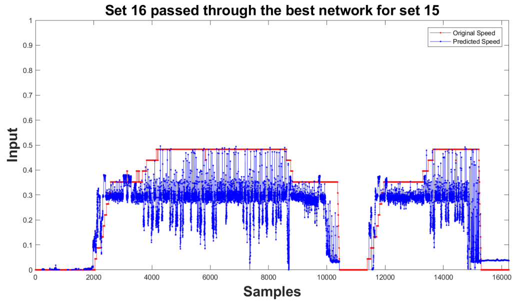


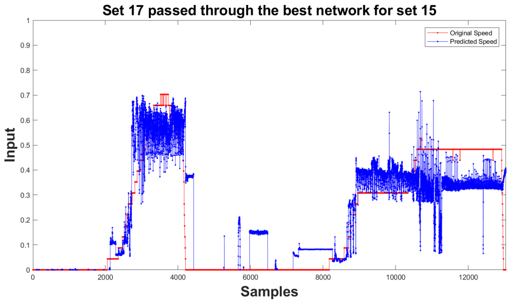


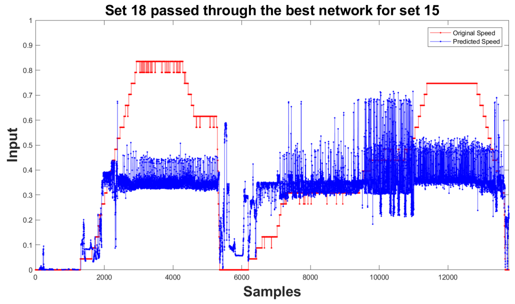


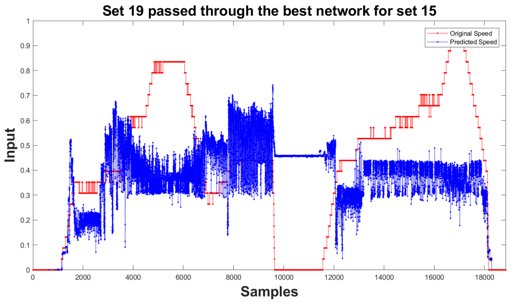


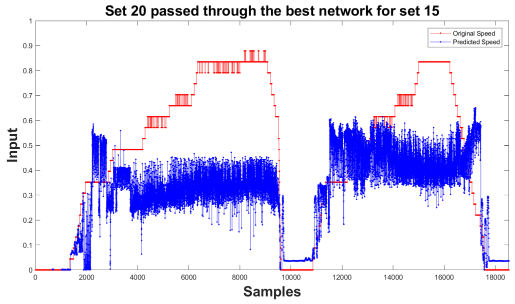

Set 15 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

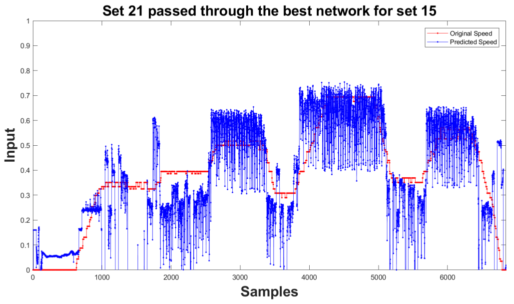

Set 16 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

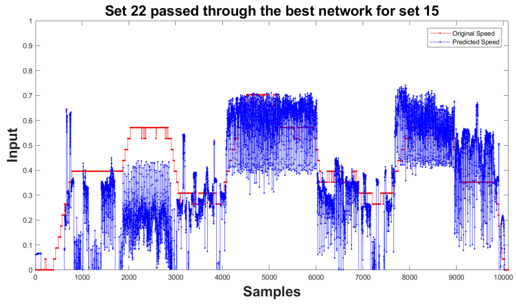

Set 17 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

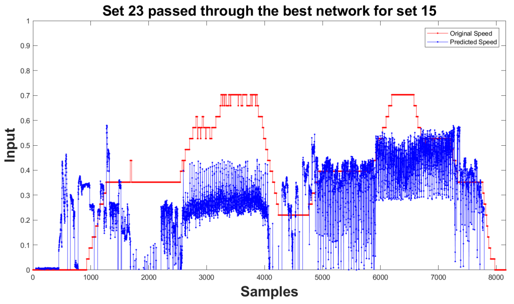

Set 18 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

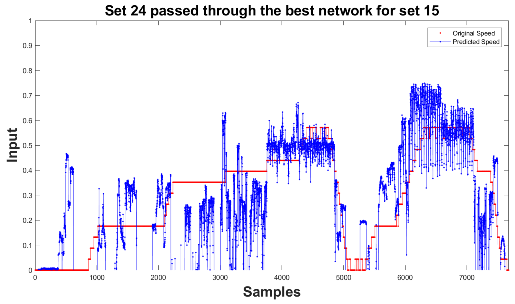

Set 19 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

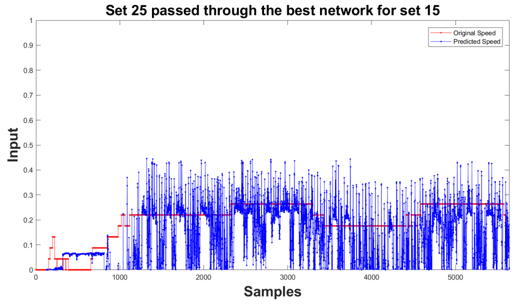

Set 20 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

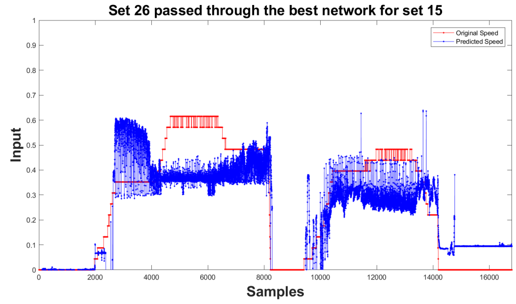

Set 21 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

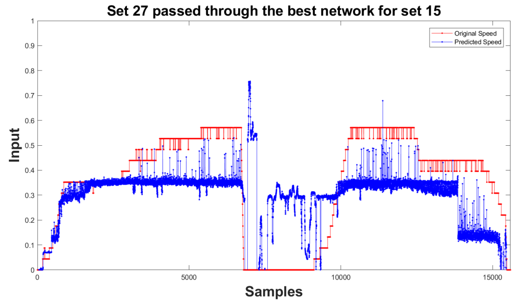

Set 22 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples


Set 23 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

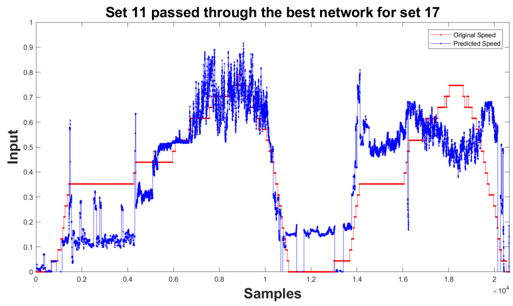

Set 24 passed through the best network for set 15
Original Speed
Predicted Speed
Input
Samples

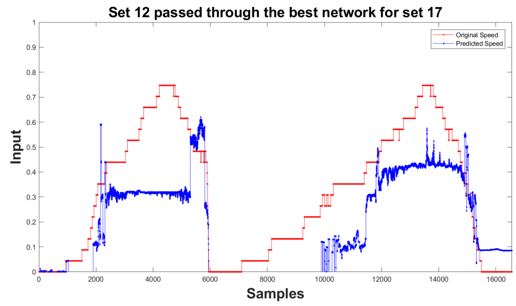


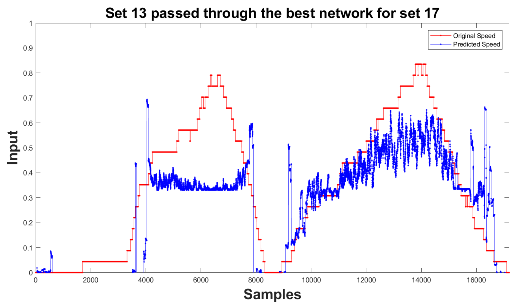


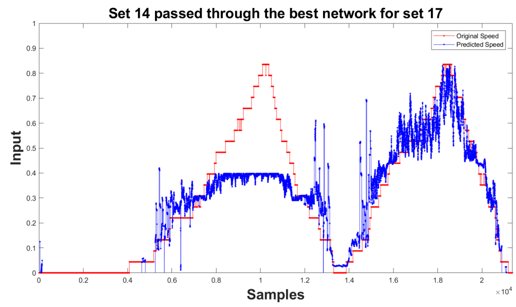


H.1.4 Network 17

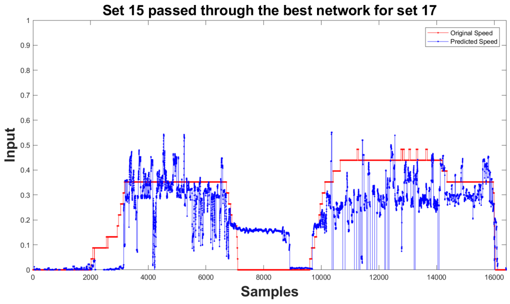




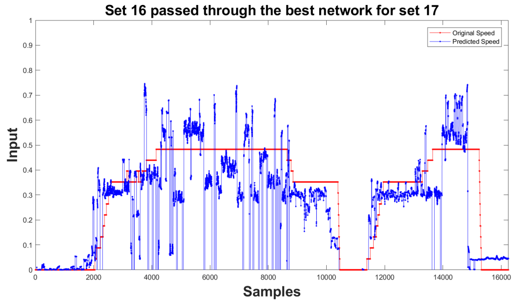




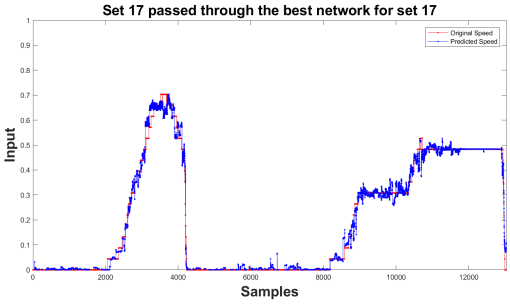
Set 15 passed through the best network for set 17



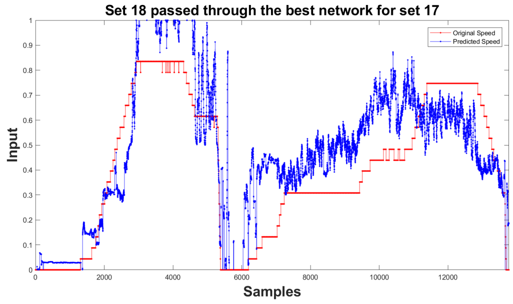
Set 16 passed through the best network for set 17



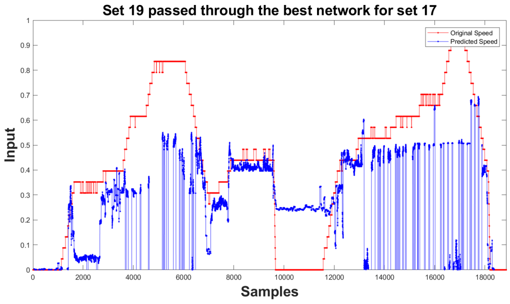
Set 17 passed through the best network for set 17



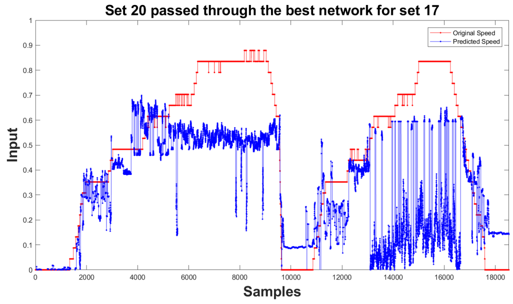
Set 18 passed through the best network for set 17



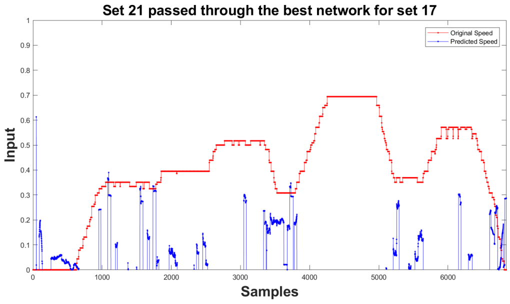
Set 19 passed through the best network for set 17



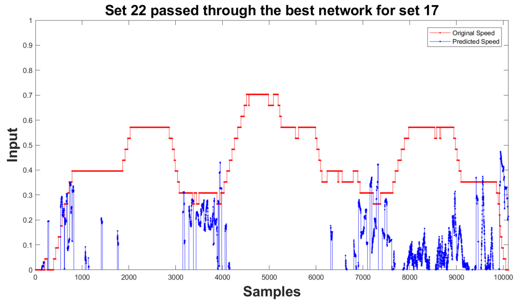
Set 20 passed through the best network for set 17



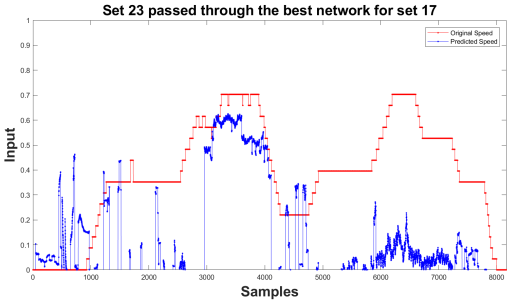
Set 21 passed through the best network for set 17



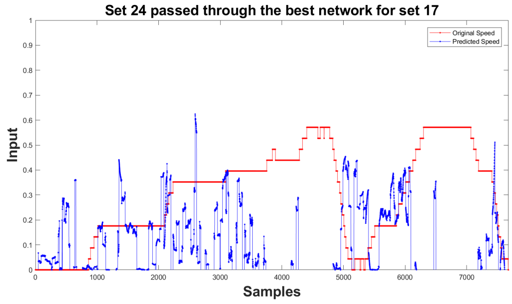
Set 22 passed through the best network for set 17

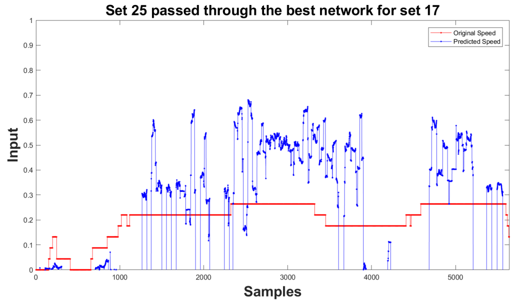


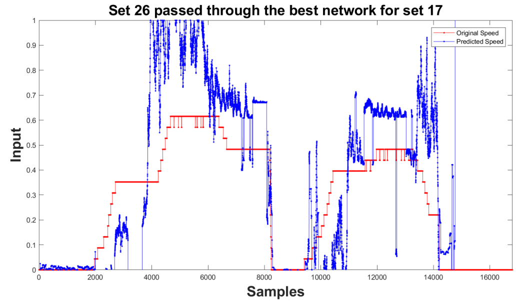
Set 23 passed through the best network for set 17

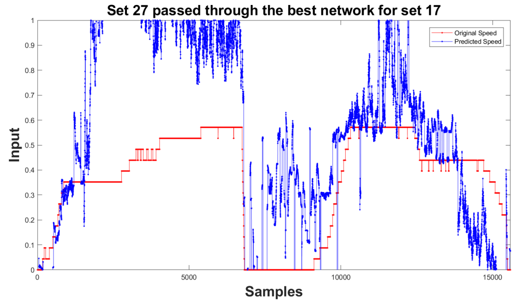


Set 24 passed through the best network for set 17

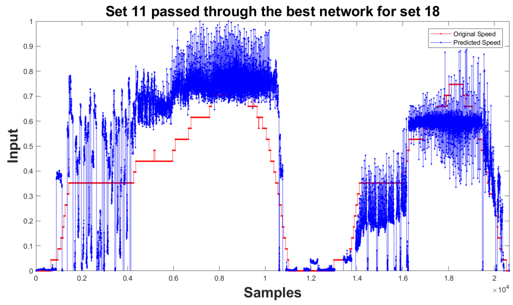


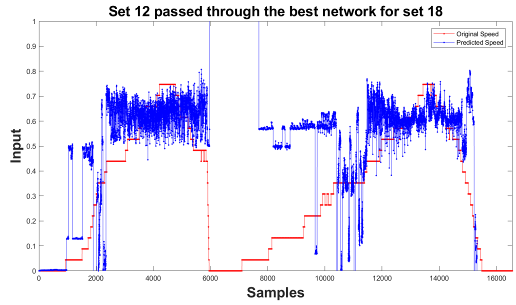


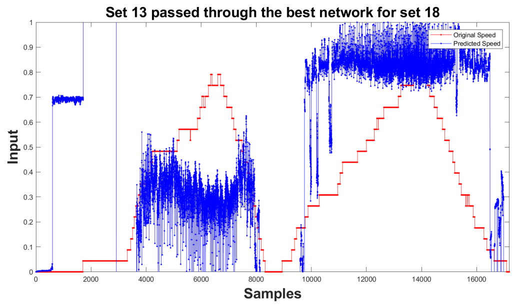


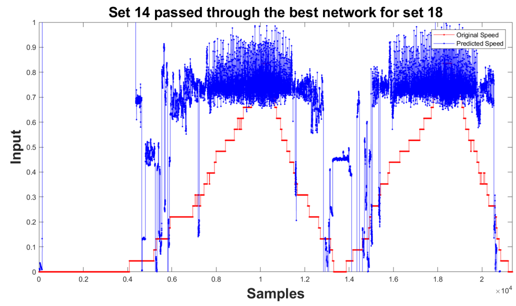


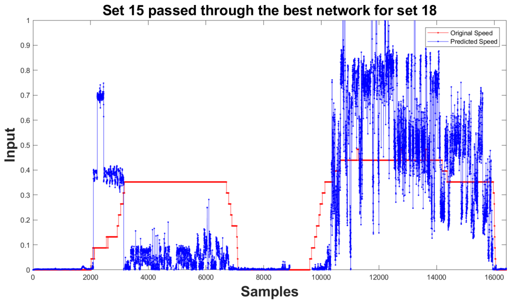
H.1.5 Network 18

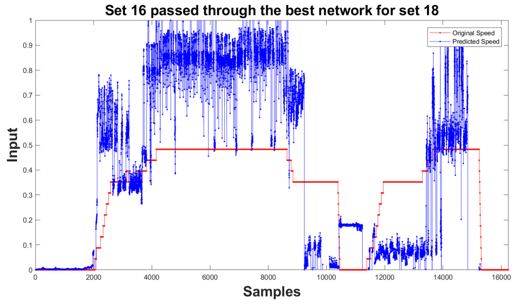


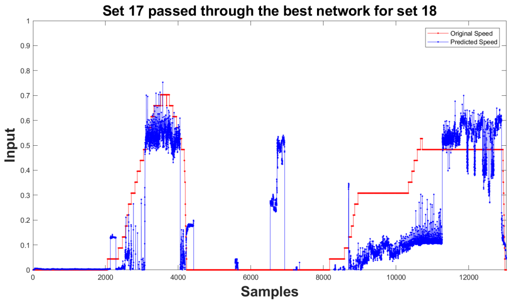


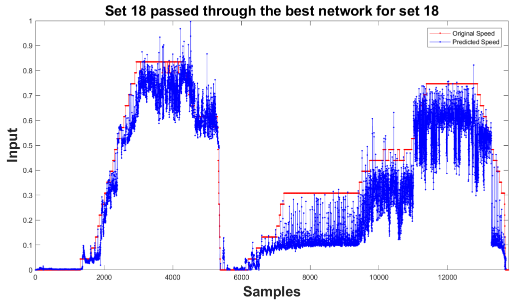


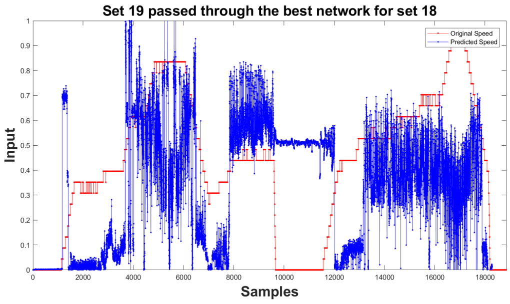


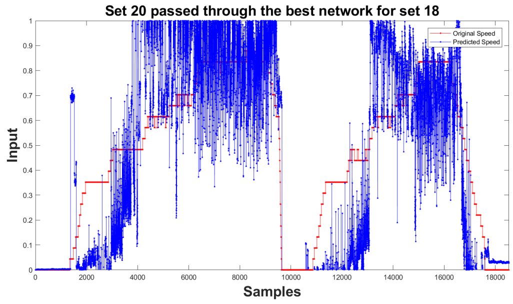

Set 15 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

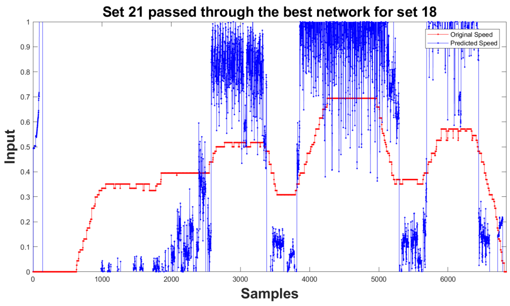

Set 16 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

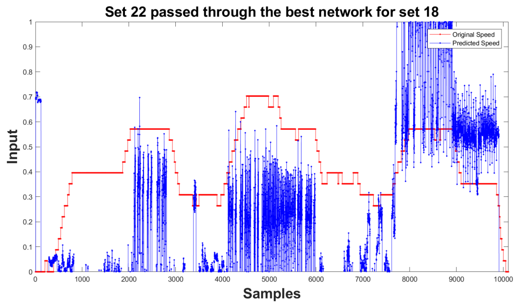

Set 17 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

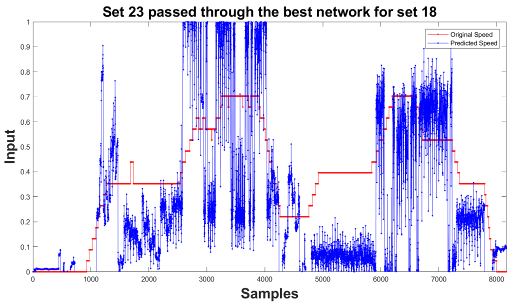

Set 18 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

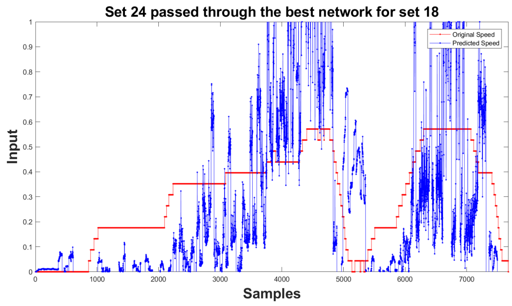

Set 19 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

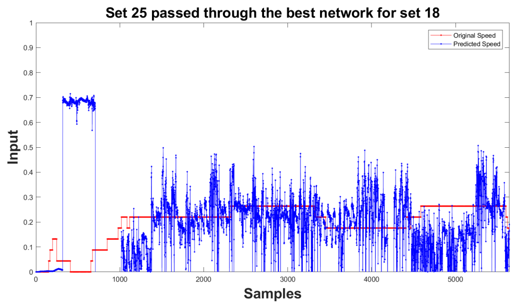

Set 20 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

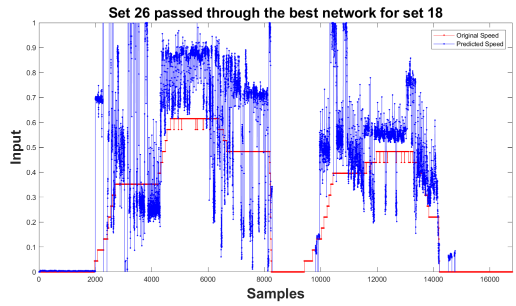

Set 21 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

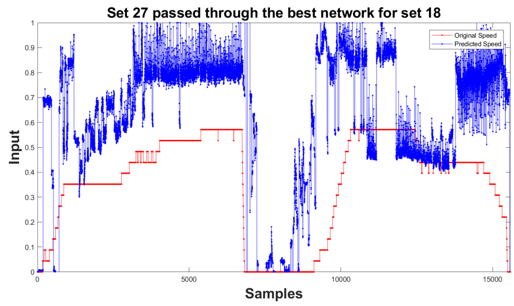

Set 22 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples


Set 23 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

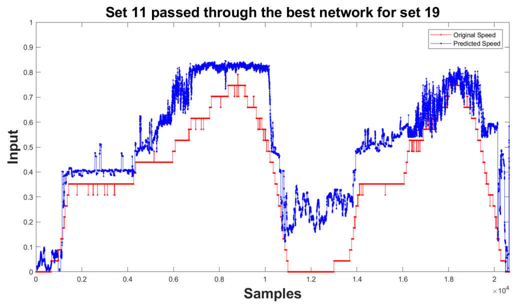

Set 24 passed through the best network for set 18
Original Speed
Predicted Speed
Input
Samples

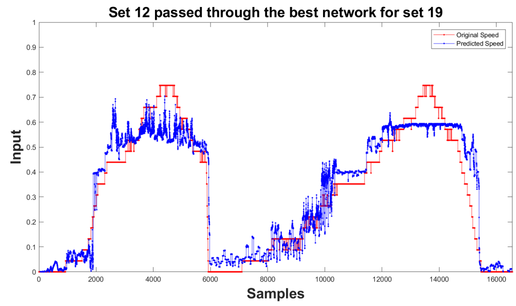


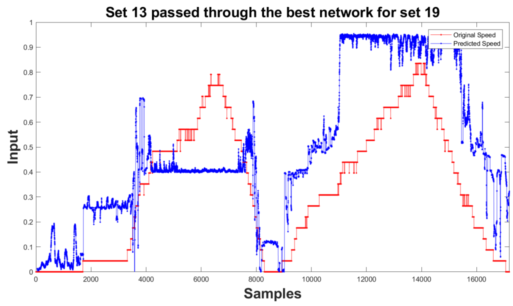


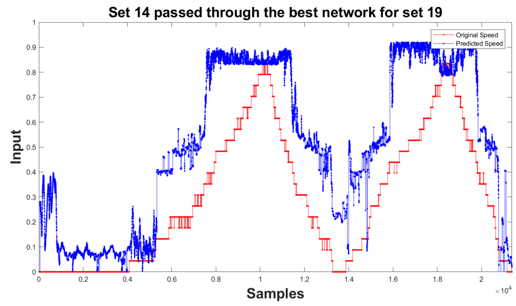


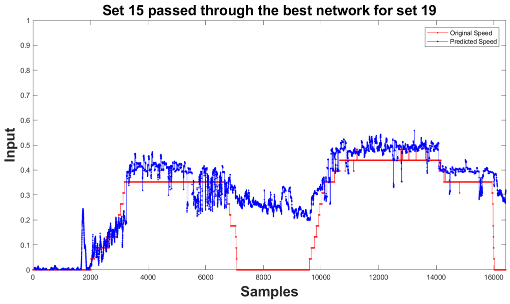
H.1.6 Network 19

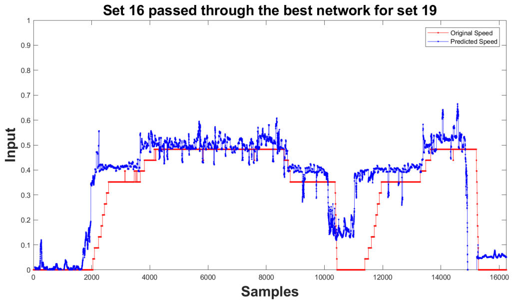


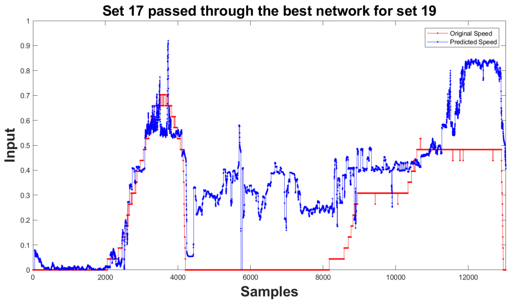


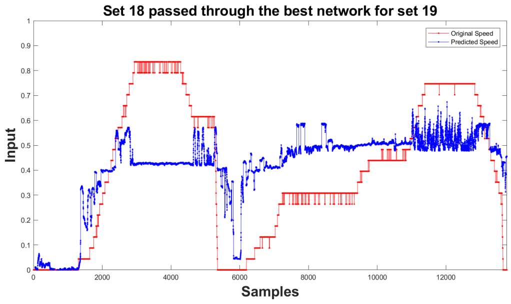


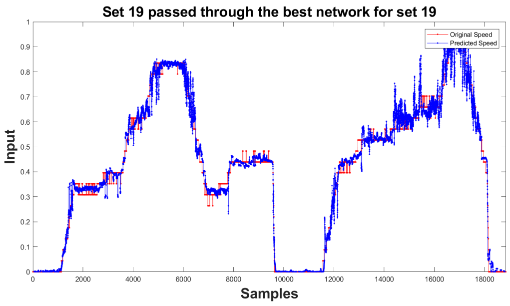


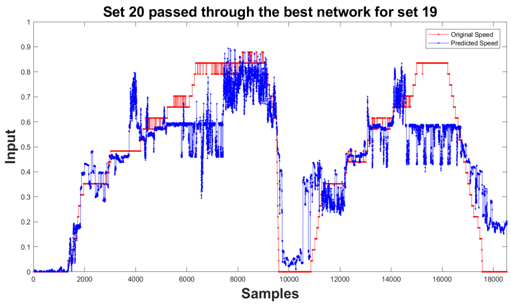

Set 15 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

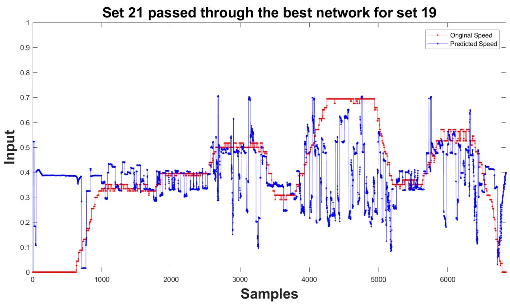

Set 16 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

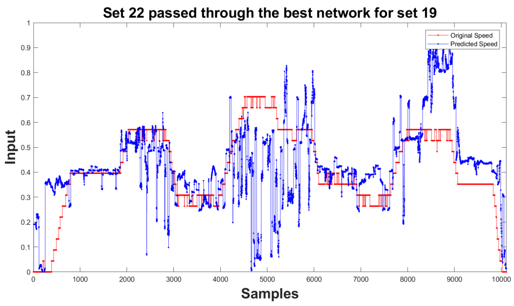

Set 17 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

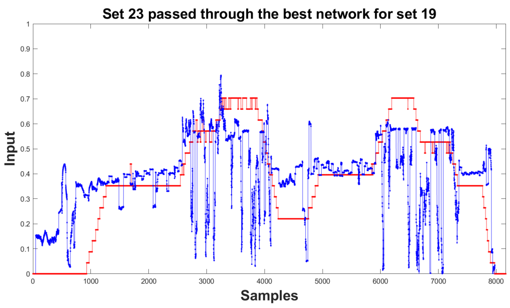

Set 18 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

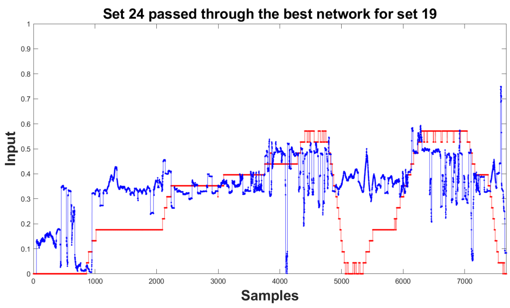

Set 19 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

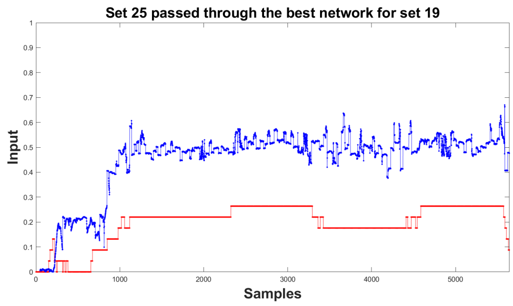

Set 20 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

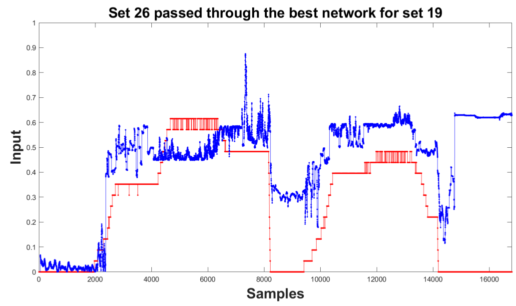

Set 21 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples

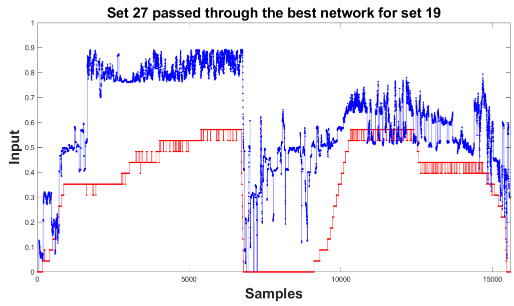

Set 22 passed through the best network for set 19
Original Speed
Predicted Speed
Input
Samples


Set 23 passed through the best network for set 19
Input
Samples

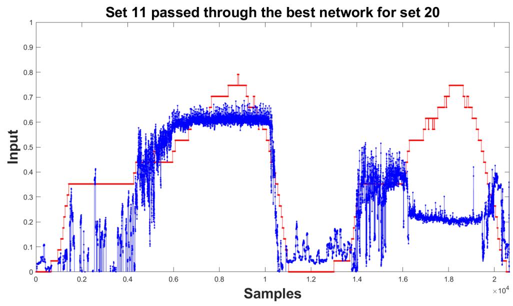

Set 24 passed through the best network for set 19
Input
Samples

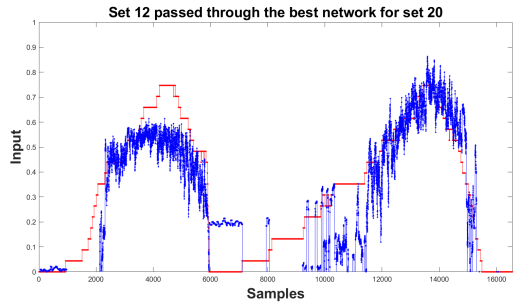


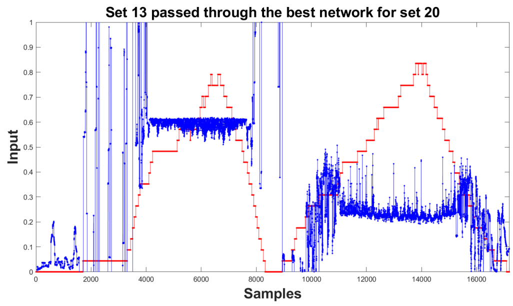


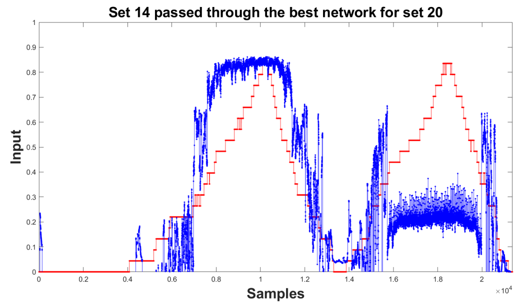


H.1.7 Network 20

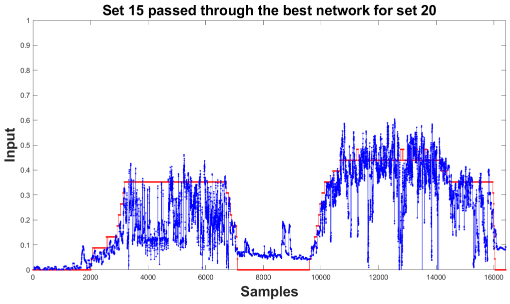




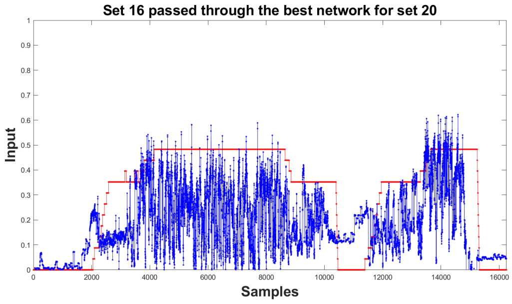




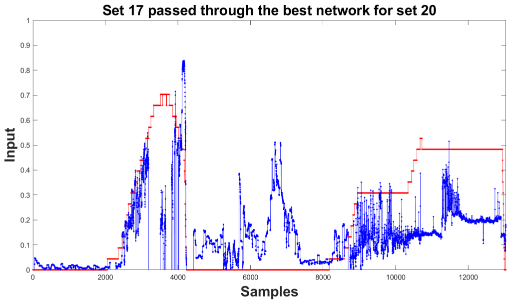
Set 15 passed through the best network for set 20



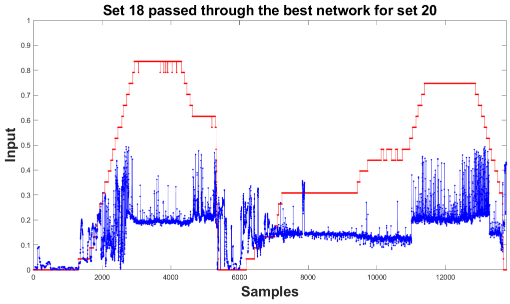
Set 16 passed through the best network for set 20



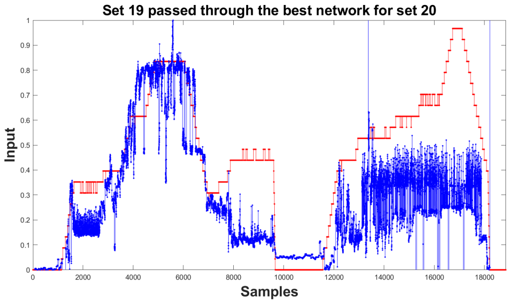
Set 17 passed through the best network for set 20



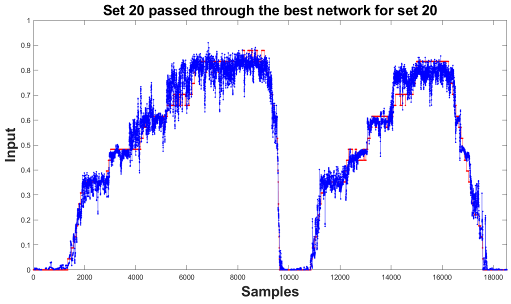
Set 18 passed through the best network for set 20



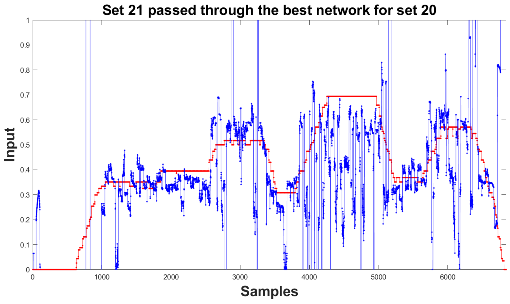
Set 19 passed through the best network for set 20



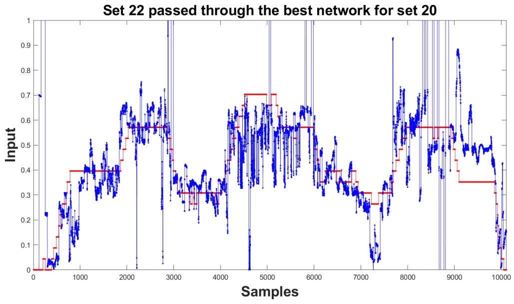
Set 20 passed through the best network for set 20



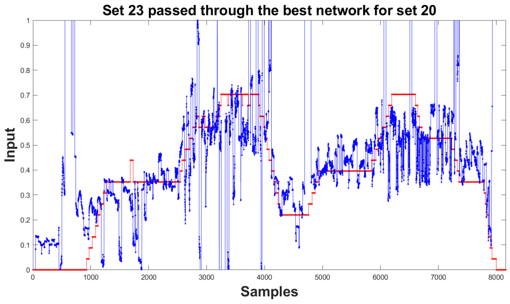
Set 21 passed through the best network for set 20



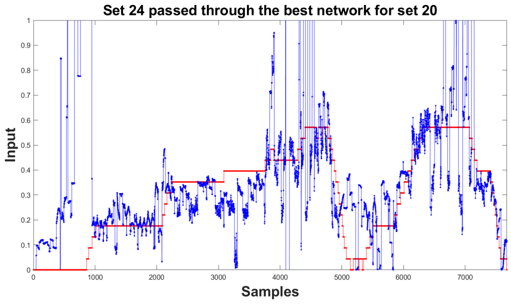
Set 22 passed through the best network for set 20

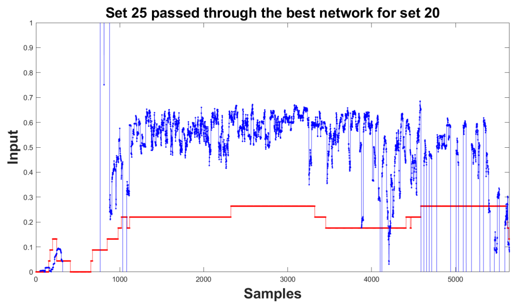


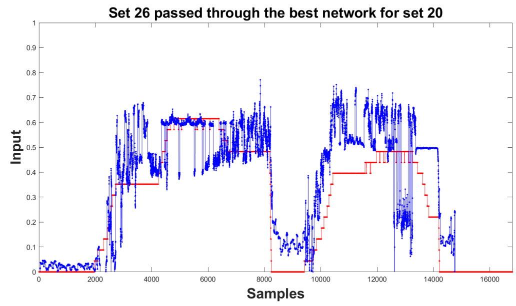
Set 23 passed through the best network for set 20

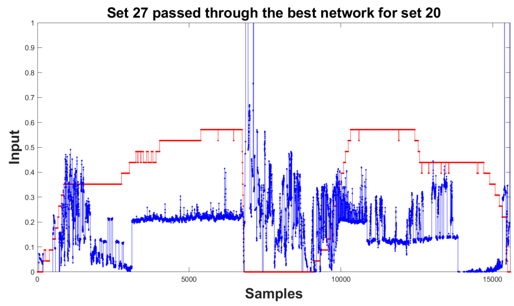


Set 24 passed through the best network for set 20

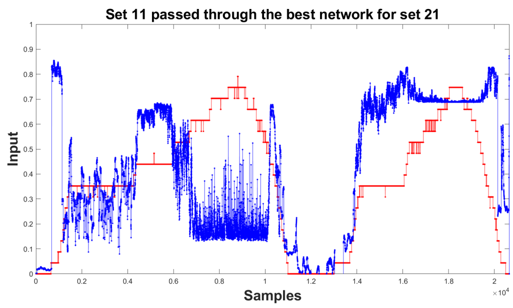


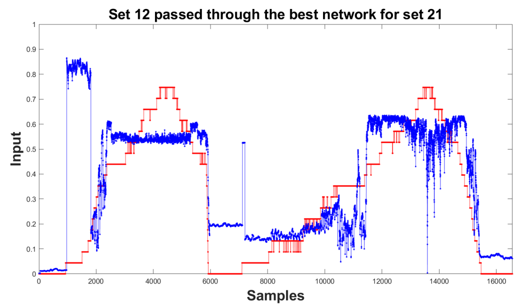


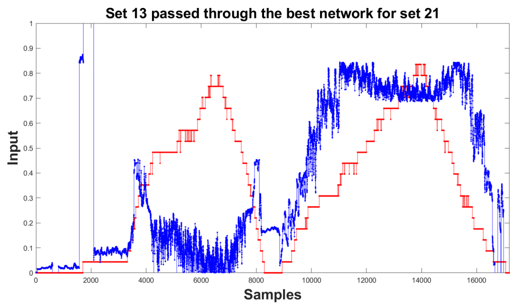


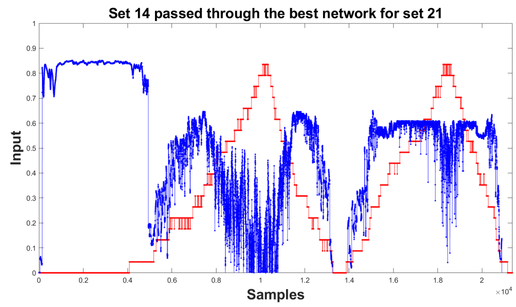


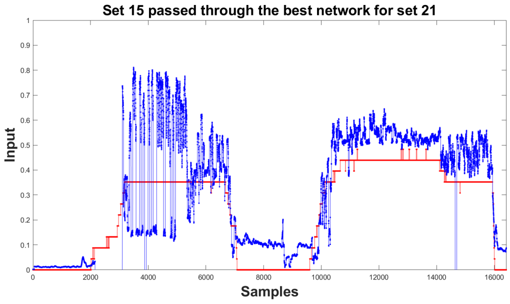
H.1.8 Network 21

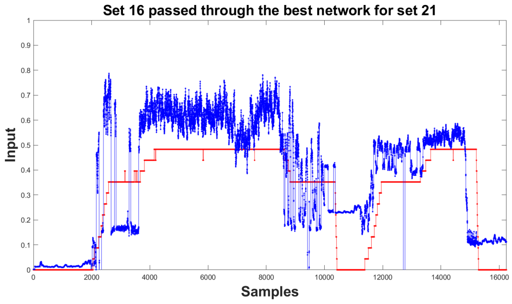


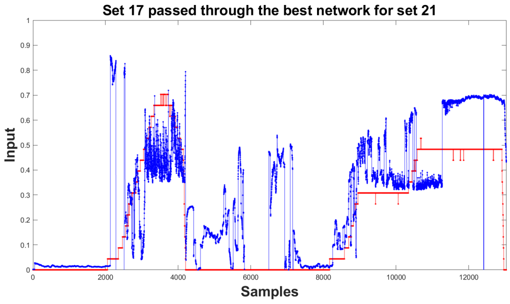


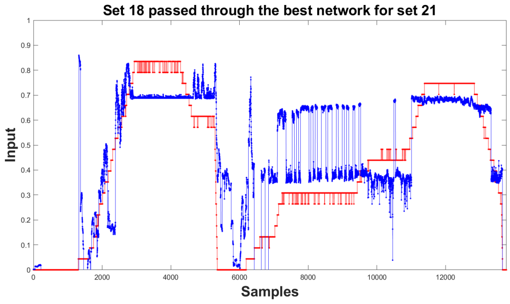


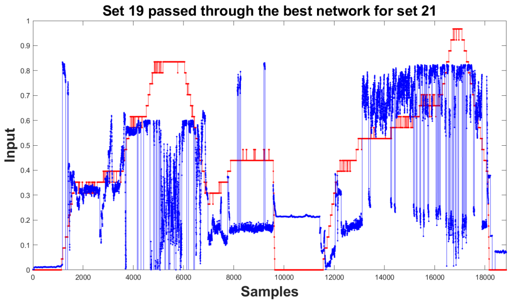


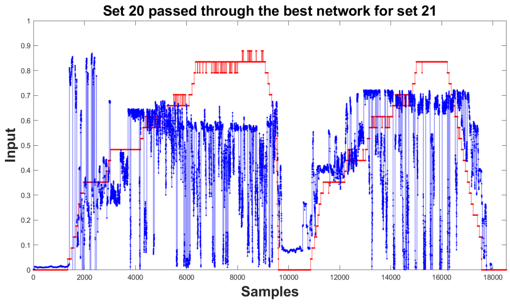

Set 15 passed through the best network for set 21
Input
Samples

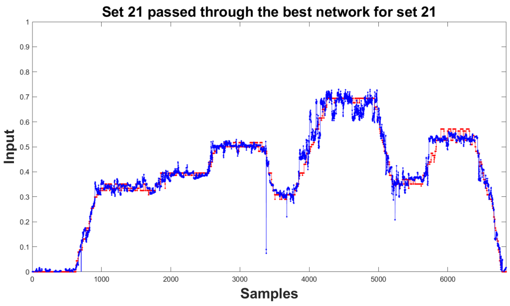

Set 16 passed through the best network for set 21
Input
Samples

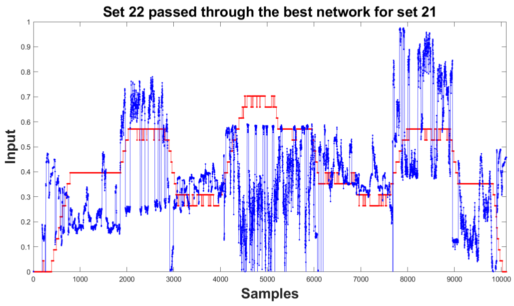

Set 17 passed through the best network for set 21
Input
Samples

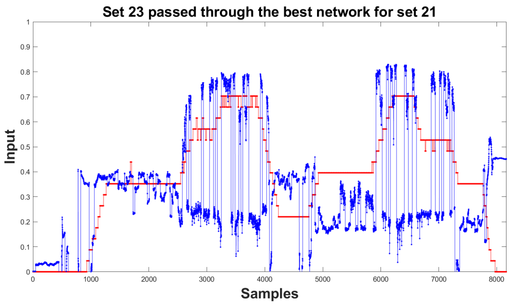

Set 18 passed through the best network for set 21
Input
Samples

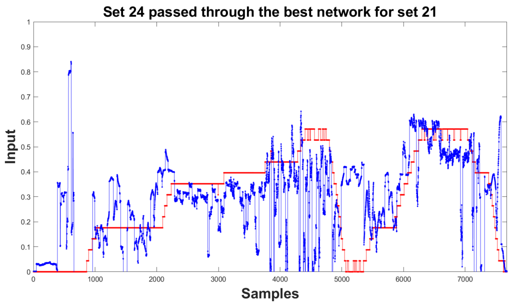

Set 19 passed through the best network for set 21
Input
Samples

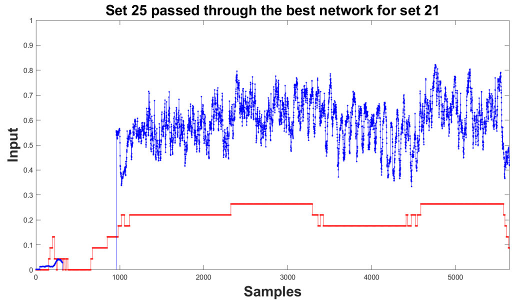

Set 20 passed through the best network for set 21
Input
Samples

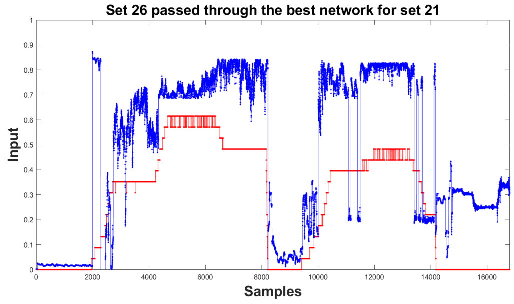

Set 21 passed through the best network for set 21
Input
Samples

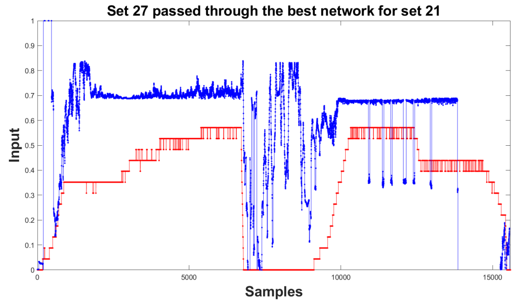

Set 22 passed through the best network for set 21
Input
Samples


Set 23 passed through the best network for set 21
Input
Samples

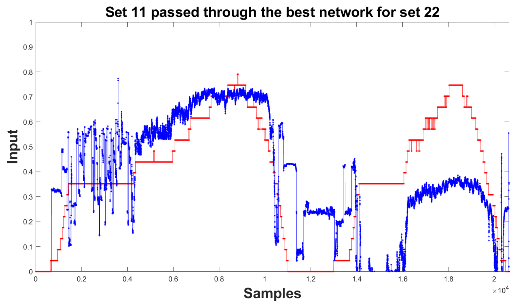

Set 24 passed through the best network for set 21
Input
Samples

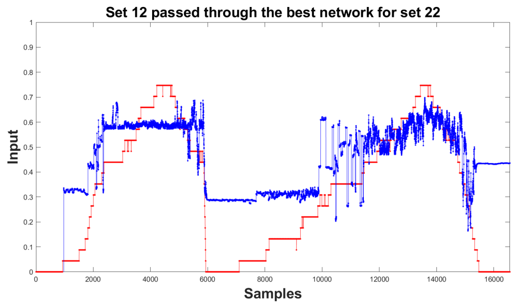


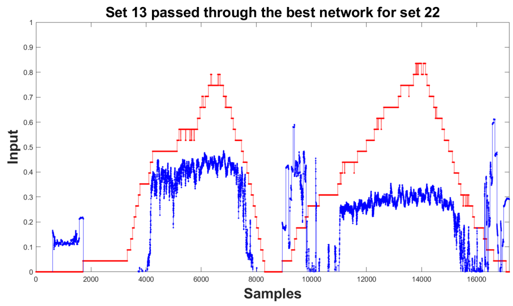


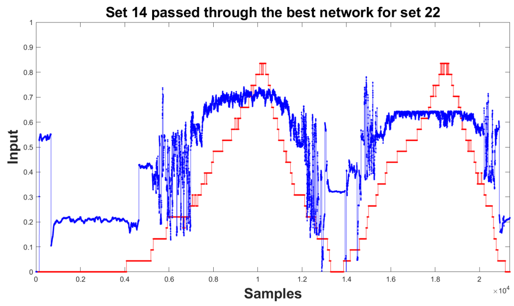


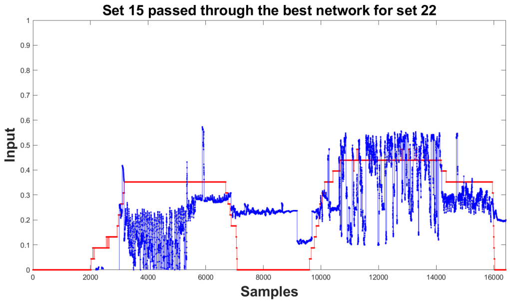
H.1.9 Network 22

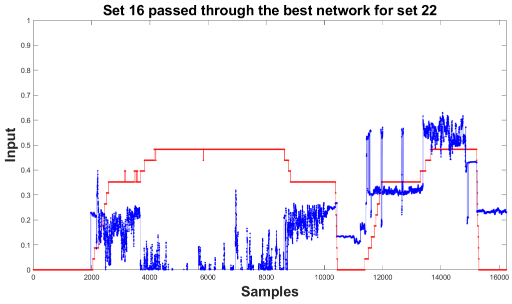


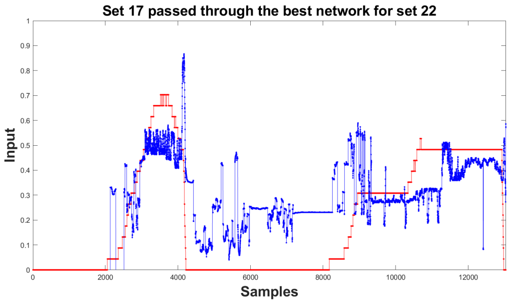


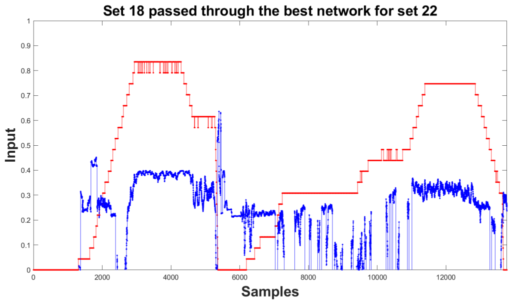


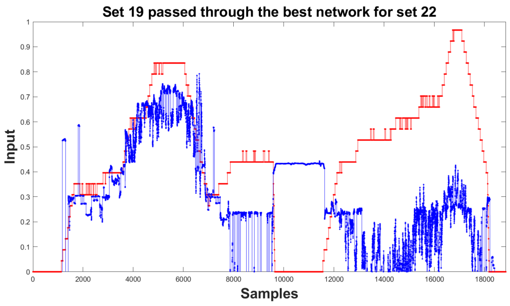


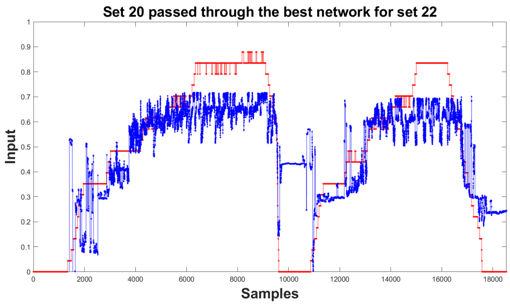

Set 15 passed through the best network for set 22
Input
Samples

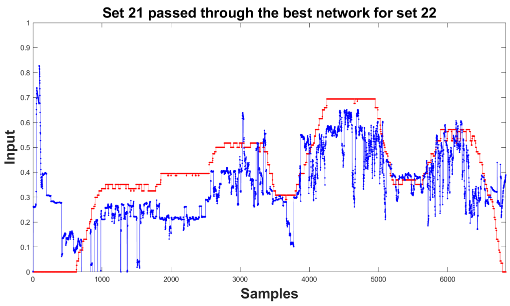

Set 16 passed through the best network for set 22
Input
Samples

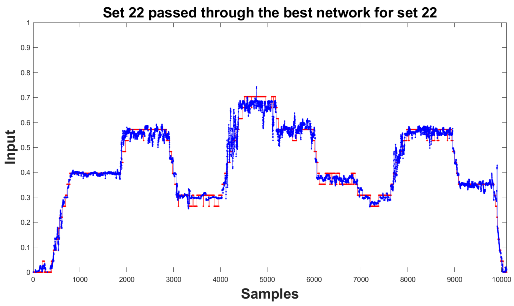

Set 17 passed through the best network for set 22
Input
Samples

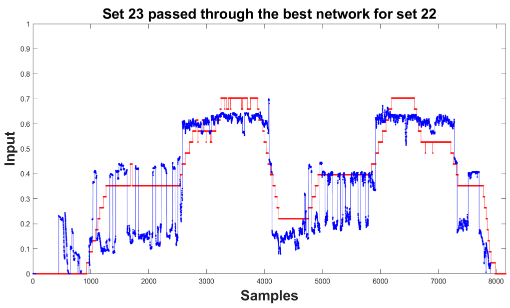

Set 18 passed through the best network for set 22
Input
Samples

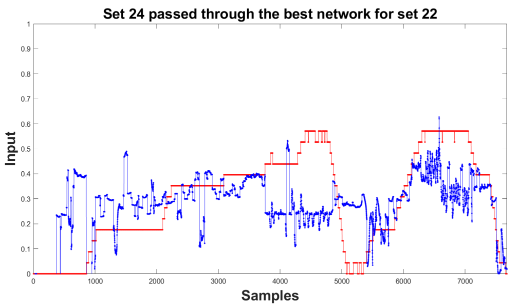

Set 19 passed through the best network for set 22
Input
Samples

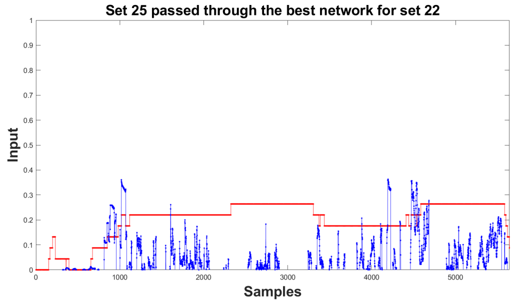

Set 20 passed through the best network for set 22
Input
Samples

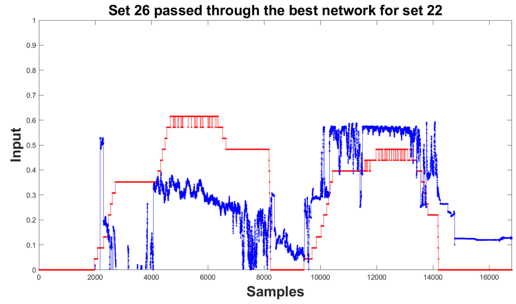

Set 21 passed through the best network for set 22
Input
Samples

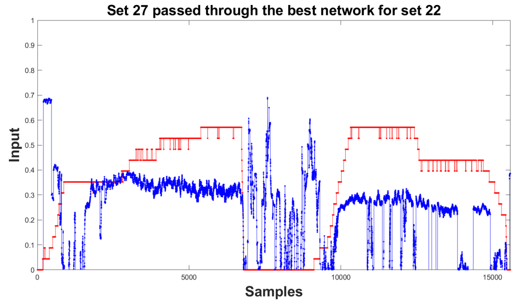

Set 22 passed through the best network for set 22
Input
Samples


Set 23 passed through the best network for set 22
Input
Samples

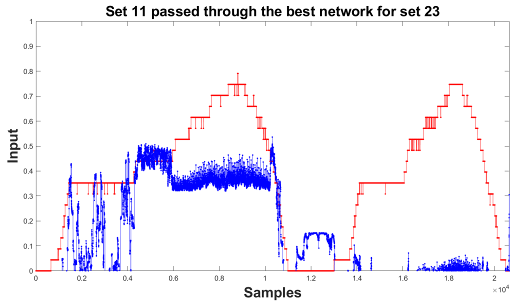

Set 24 passed through the best network for set 22
Input
Samples

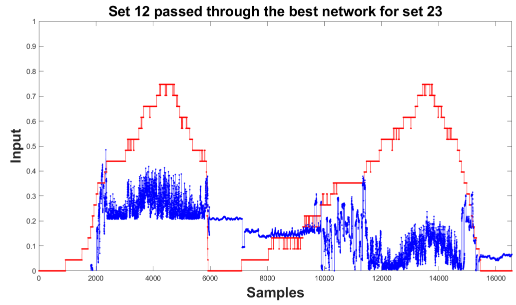


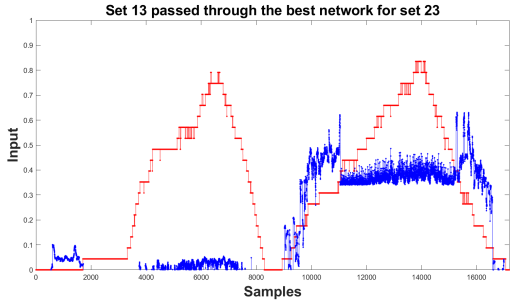


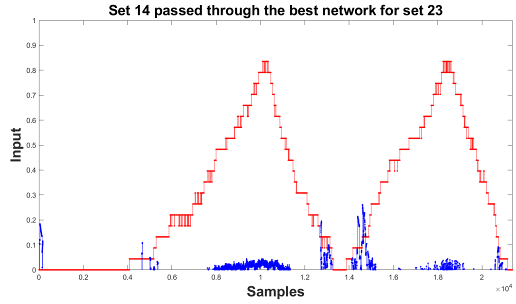


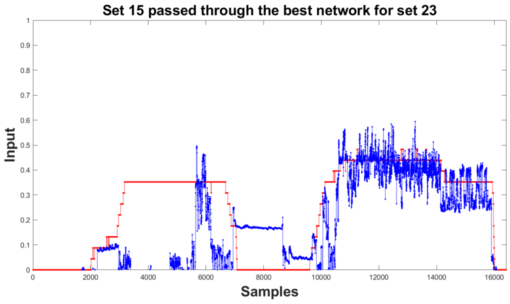
H.1.10 Network 23

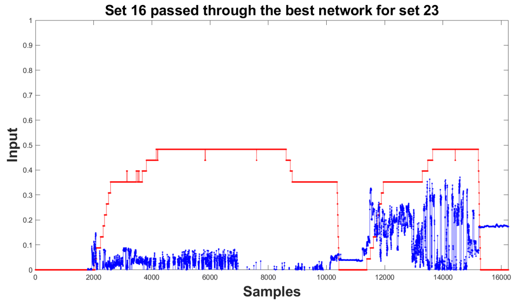


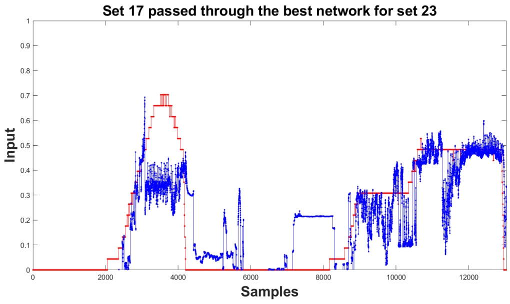


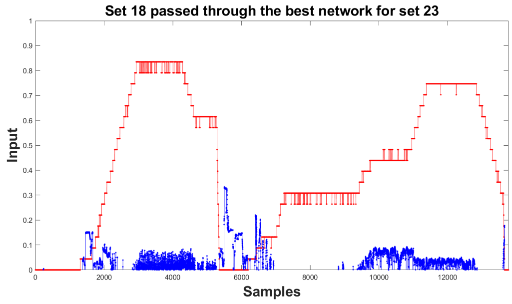


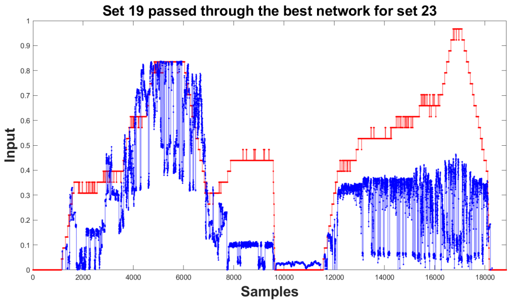


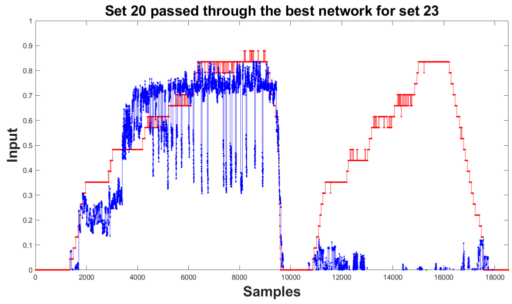

Set 15 passed through the best network for set 23
Input
Samples

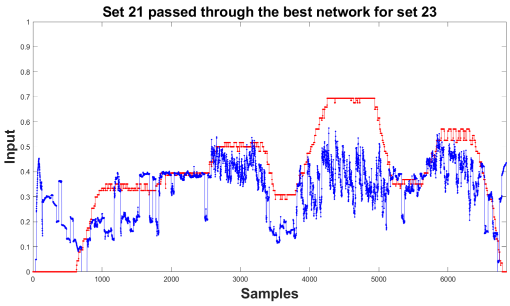

Set 16 passed through the best network for set 23
Input
Samples

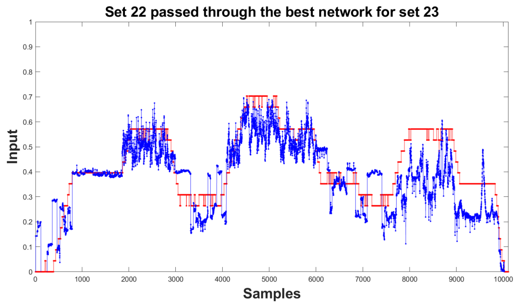

Set 17 passed through the best network for set 23
Input
Samples

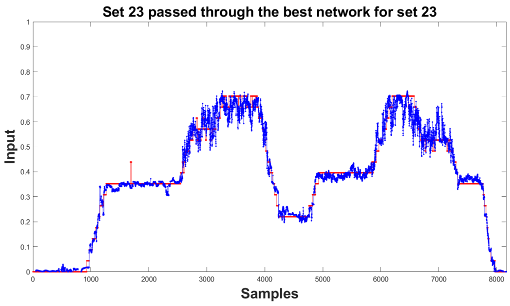

Set 18 passed through the best network for set 23
Input
Samples

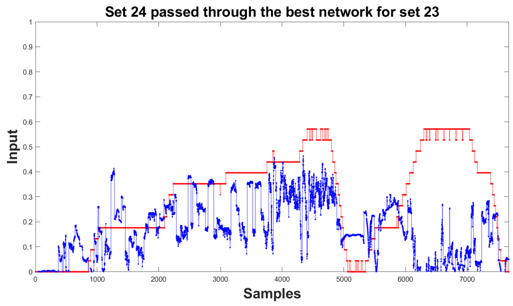

Set 19 passed through the best network for set 23
Input
Samples

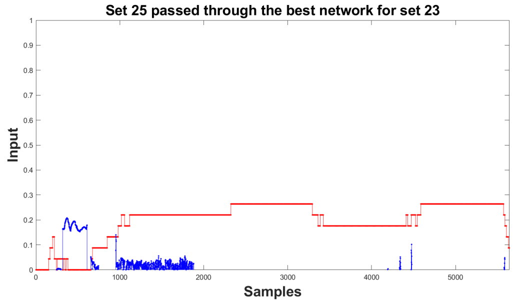

Set 20 passed through the best network for set 23
Input
Samples

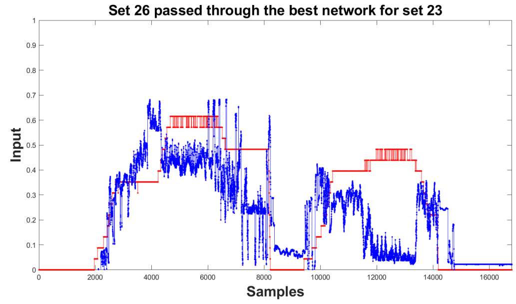

Set 21 passed through the best network for set 23
Input
Samples

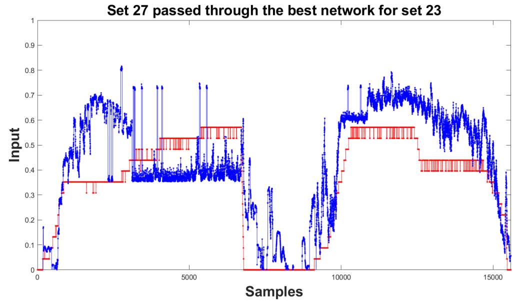

Set 22 passed through the best network for set 23
Input
Samples


Set 23 passed through the best network for set 23
Input
Samples

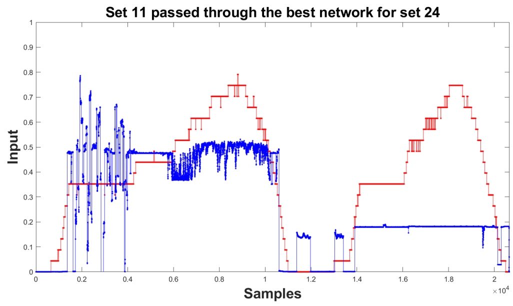

Set 24 passed through the best network for set 23
Input
Samples

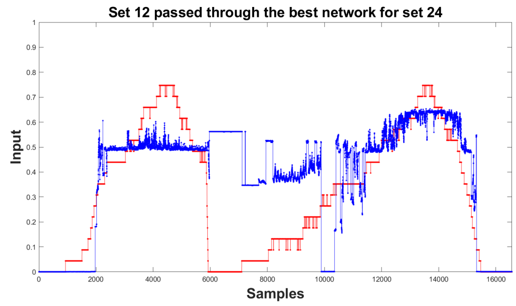


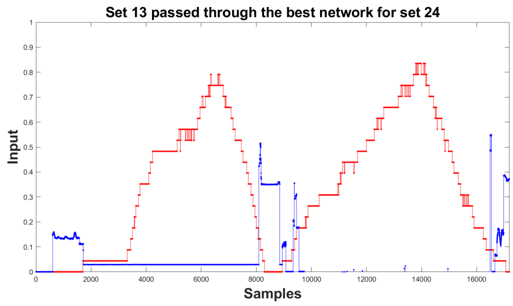


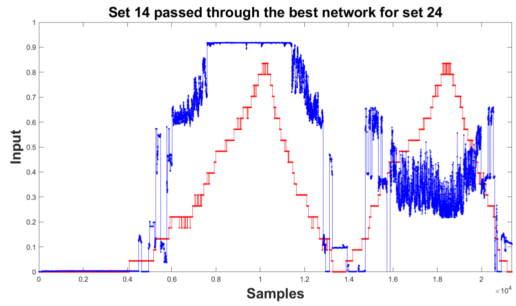


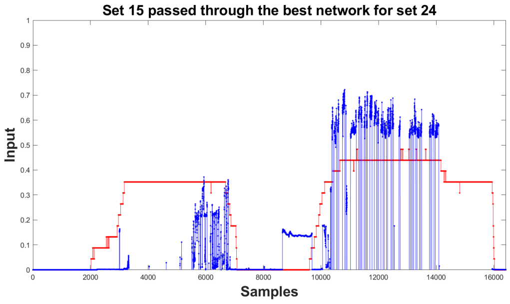
H.1.11 Network 24

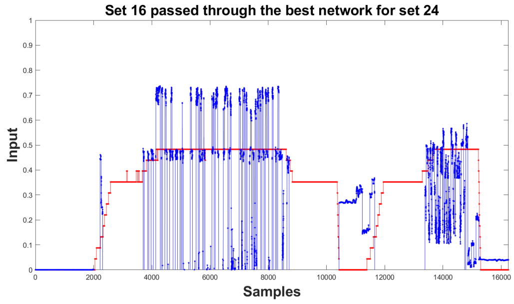


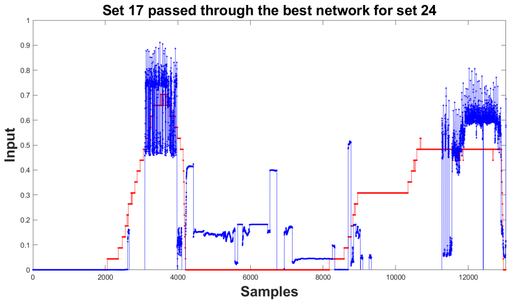


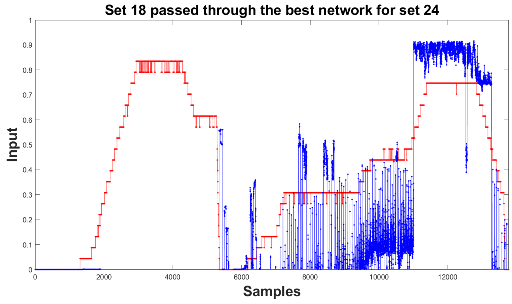


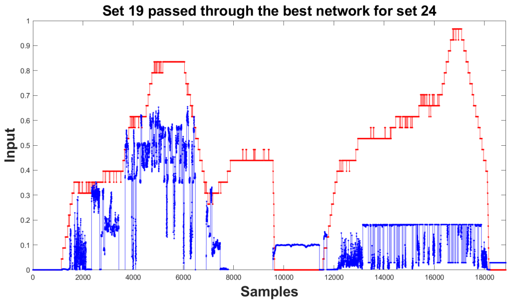


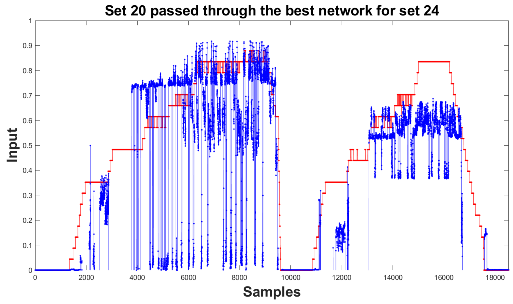

Set 15 passed through the best network for set 24
Input
Samples

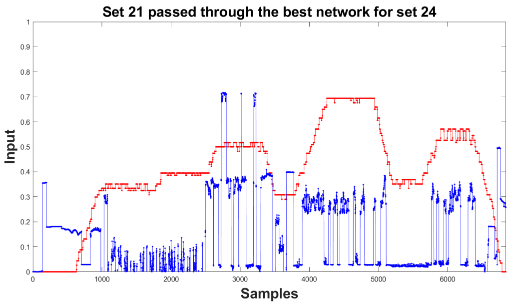

Set 16 passed through the best network for set 24
Input
Samples

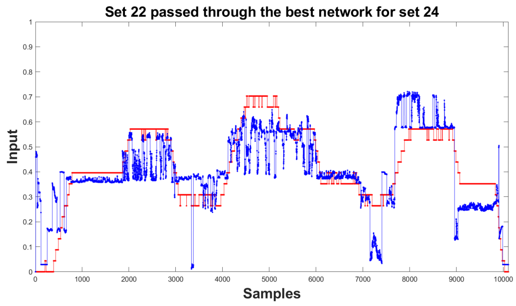

Set 17 passed through the best network for set 24
Input
Samples

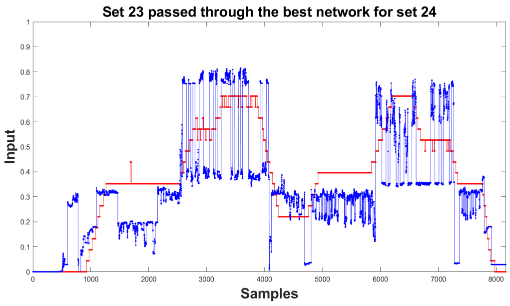

Set 18 passed through the best network for set 24
Input
Samples

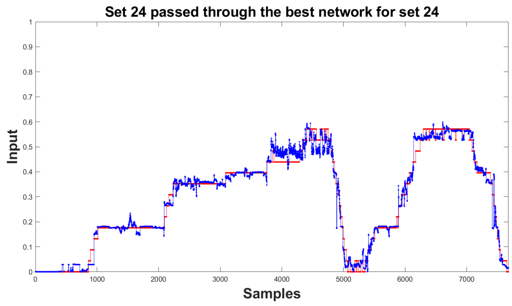

Set 19 passed through the best network for set 24
Input
Samples

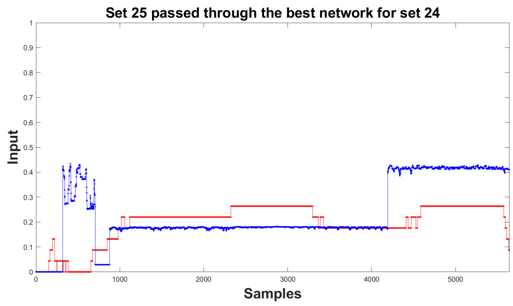

Set 20 passed through the best network for set 24
Input
Samples

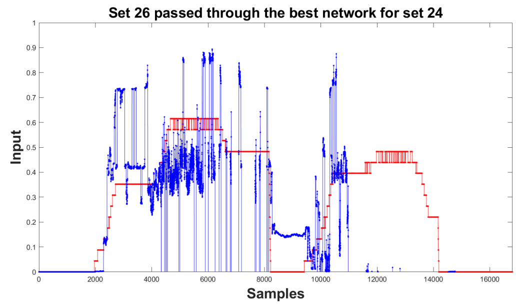

Set 21 passed through the best network for set 24
Input
Samples

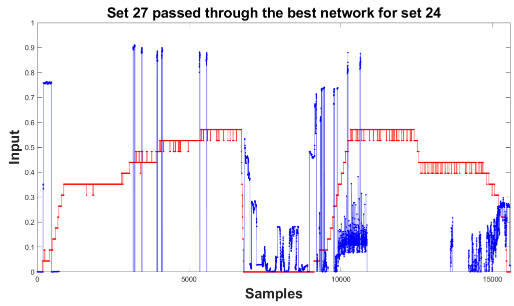

Set 22 passed through the best network for set 24
Input
Samples


Set 23 passed through the best network for set 24
Input
Samples


Set 24 passed through the best network for set 24
Input
Samples

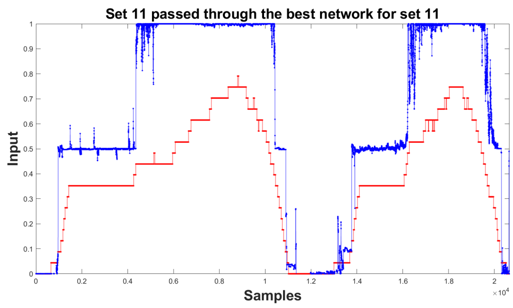


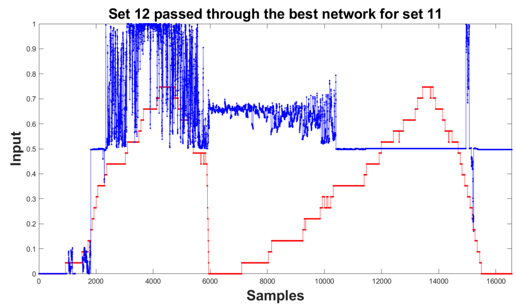


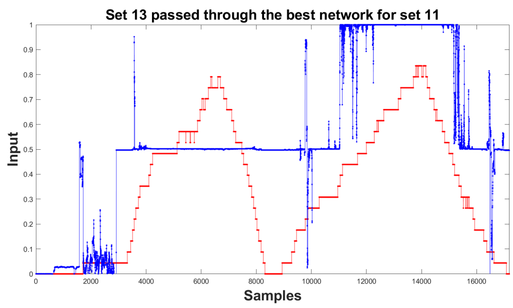


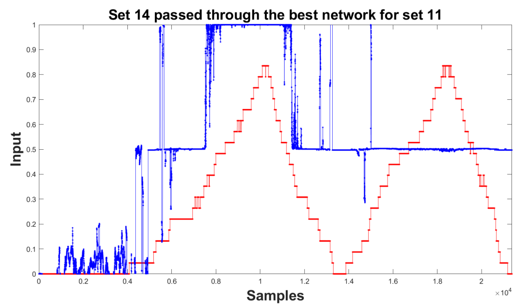
H.2 Movement State

H.2.1 Network 11

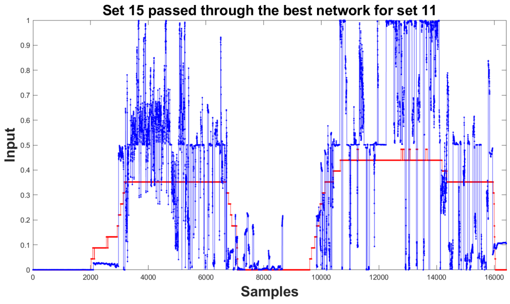




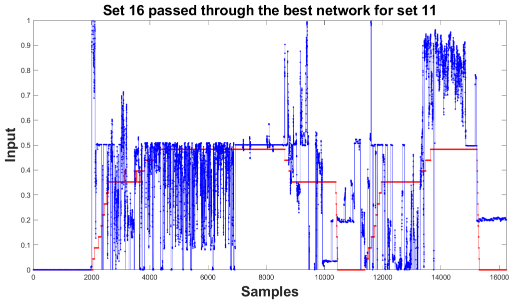




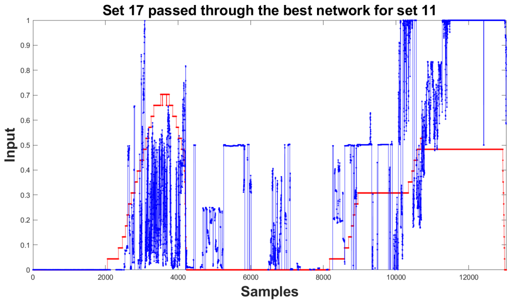
Set 15 passed through the best network for set 11



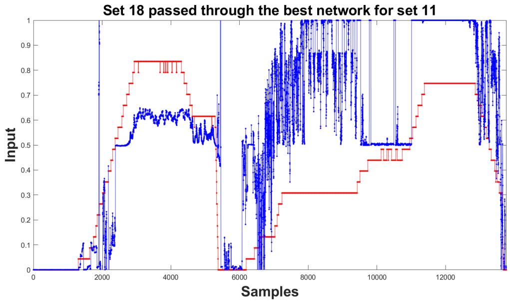
Set 16 passed through the best network for set 11



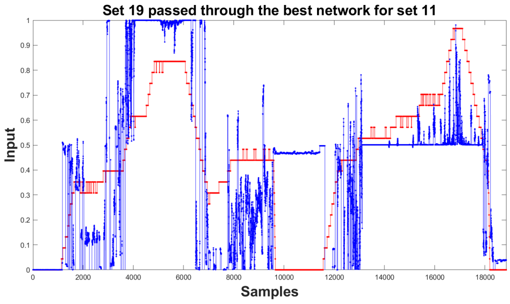
Set 17 passed through the best network for set 11



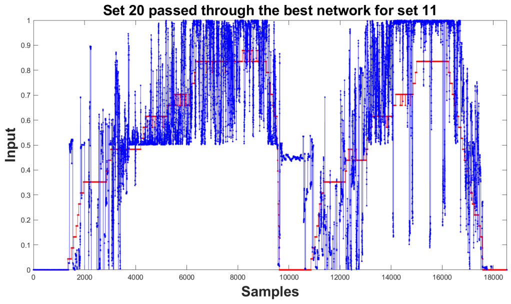
Set 18 passed through the best network for set 11



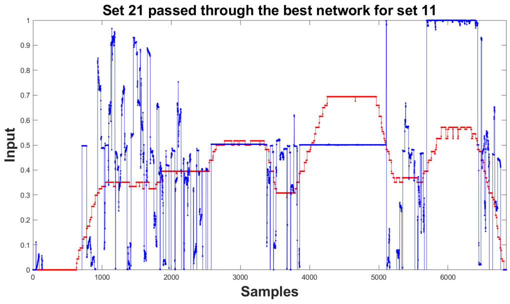
Set 19 passed through the best network for set 11



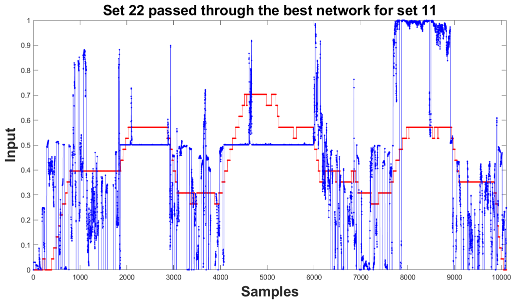
Set 20 passed through the best network for set 11



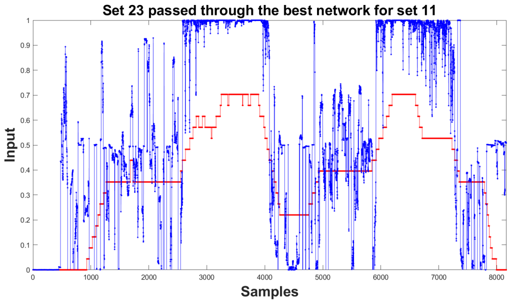
Set 21 passed through the best network for set 11



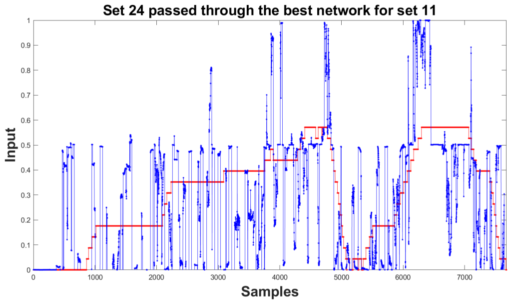
Set 22 passed through the best network for set 11

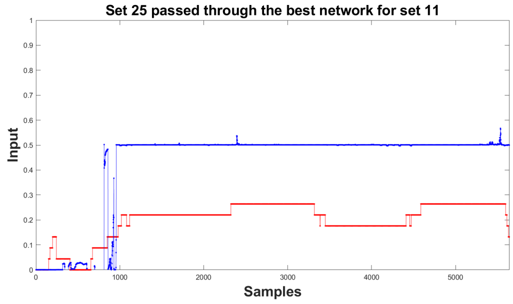


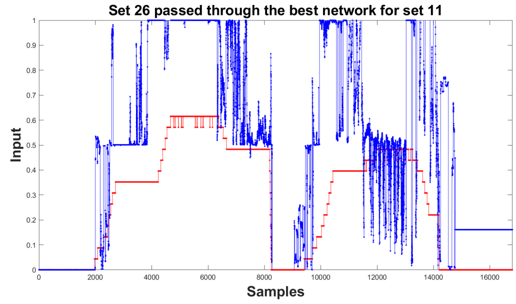
Set 23 passed through the best network for set 11

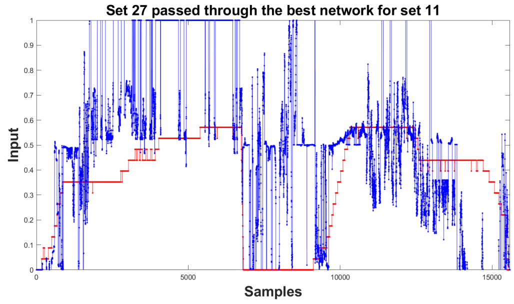


Set 24 passed through the best network for set 11

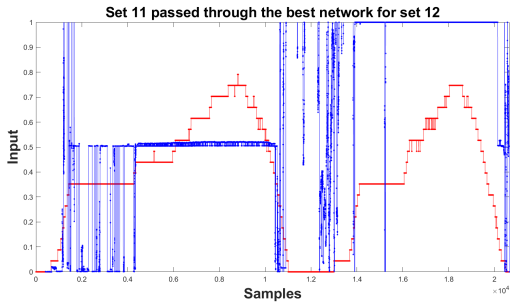


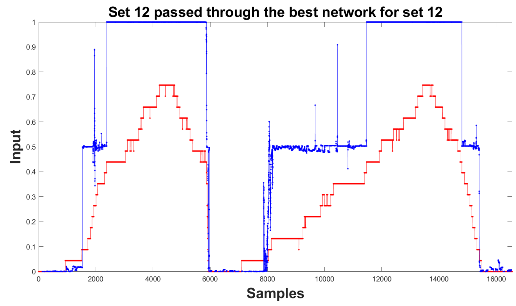


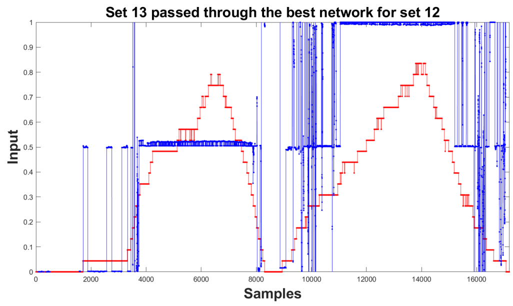


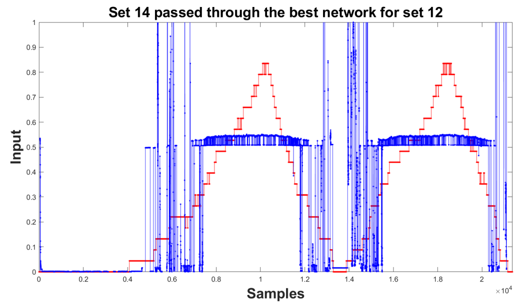


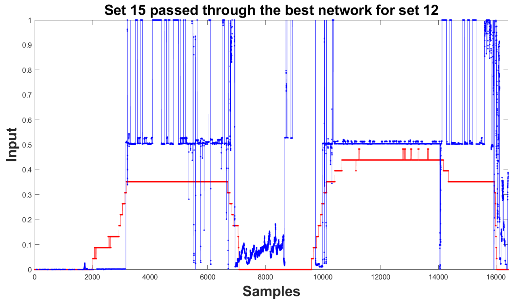
H.2.2 Network 12

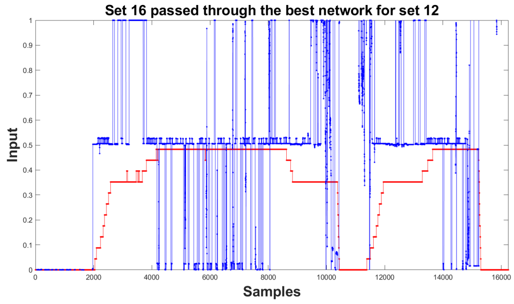


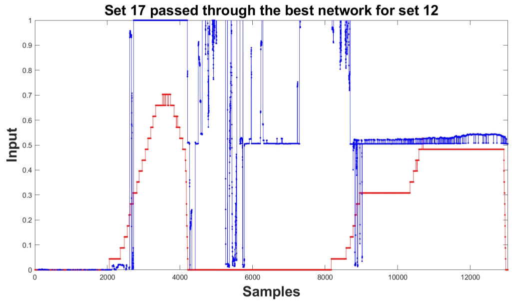


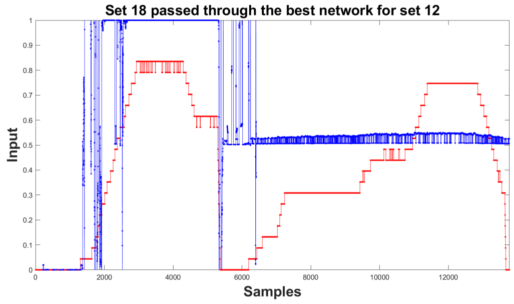


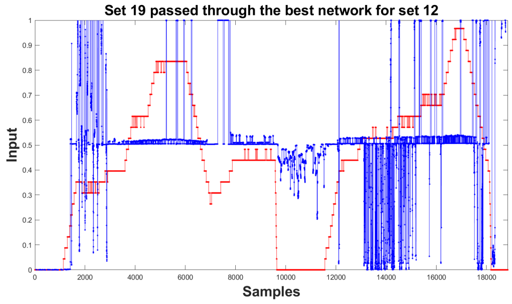


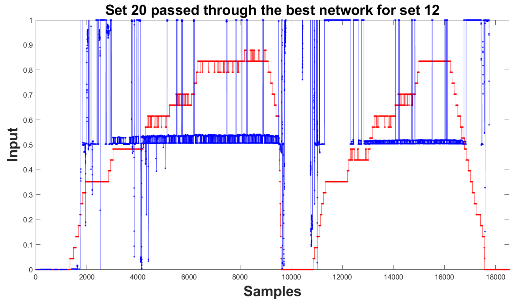

Set 15 passed through the best network for set 12
Input
Samples

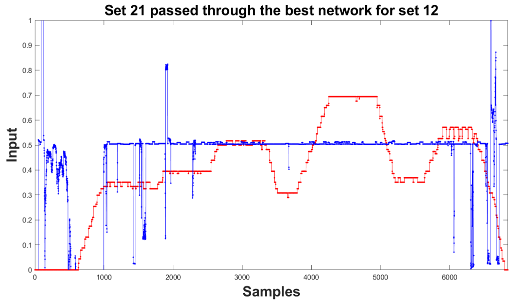

Set 16 passed through the best network for set 12
Input
Samples

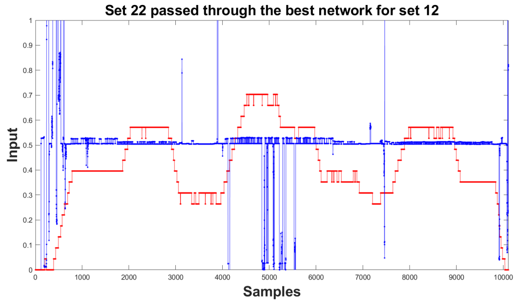

Set 17 passed through the best network for set 12
Input
Samples

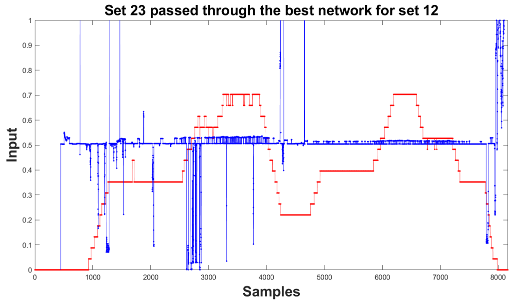

Set 18 passed through the best network for set 12
Input
Samples

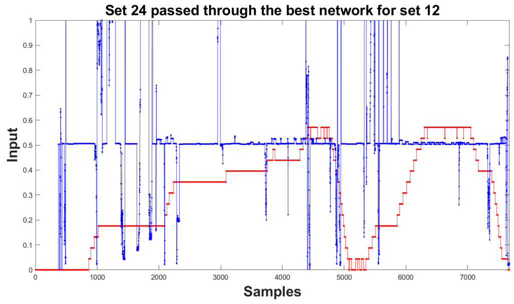

Set 19 passed through the best network for set 12
Input
Samples

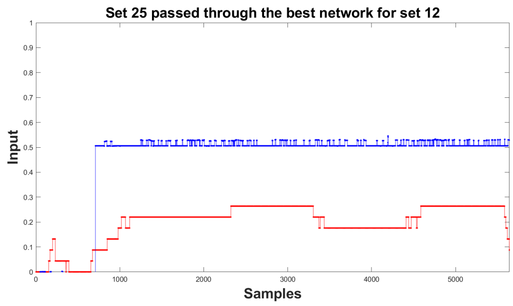

Set 20 passed through the best network for set 12
Input
Samples

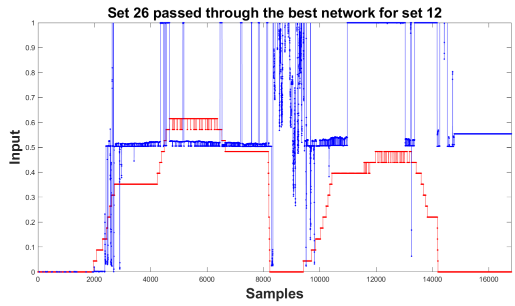

Set 21 passed through the best network for set 12
Input
Samples

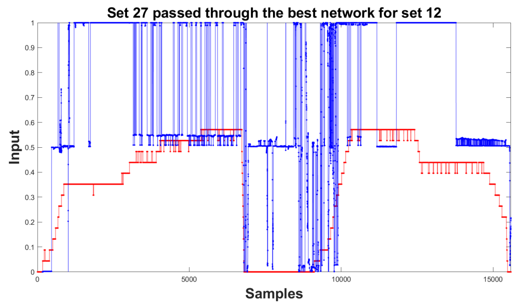

Set 22 passed through the best network for set 12
Input
Samples


Set 23 passed through the best network for set 12
Input
Samples

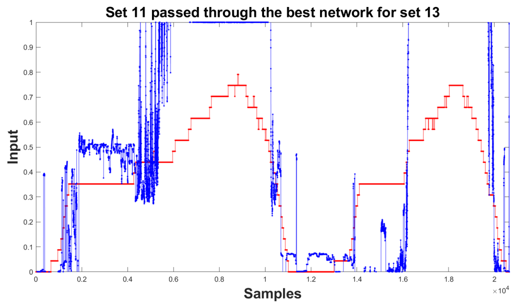

Set 24 passed through the best network for set 12
Input
Samples

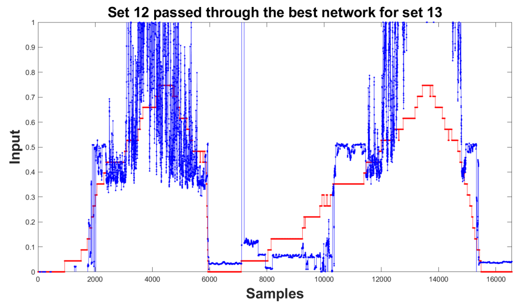


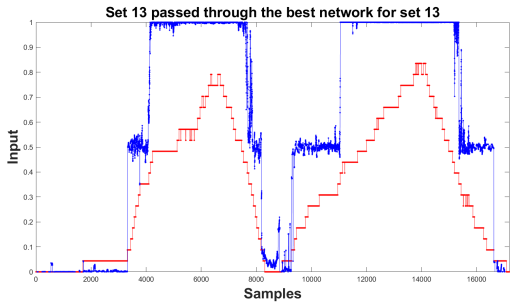


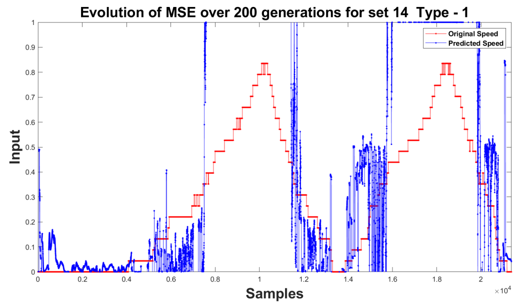


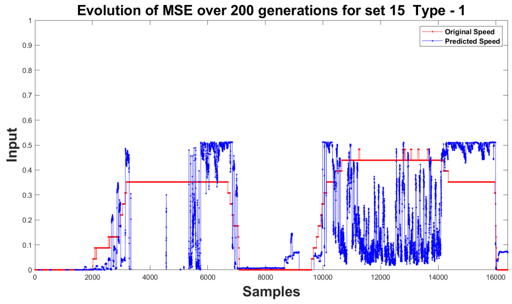
H.2.3 Network 13

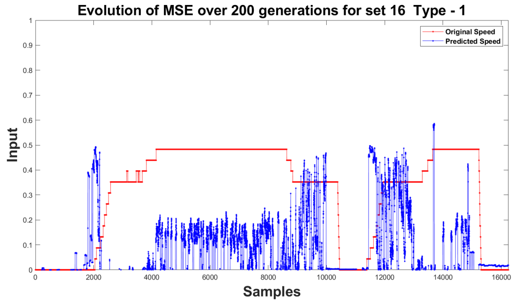


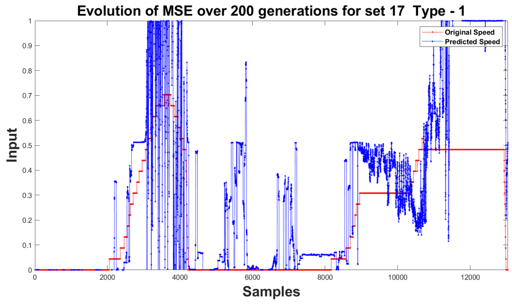


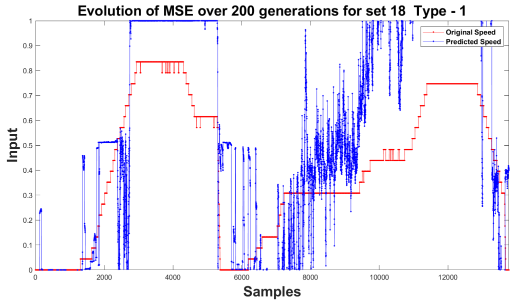


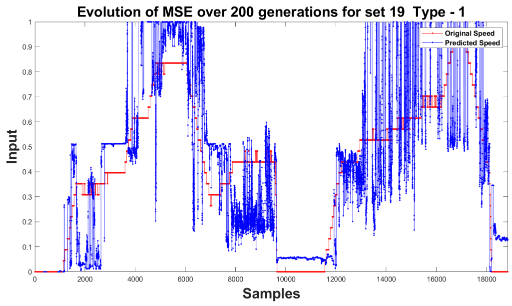


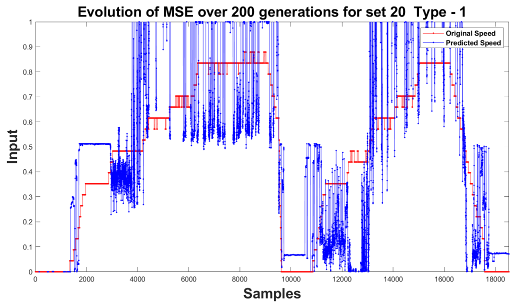

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

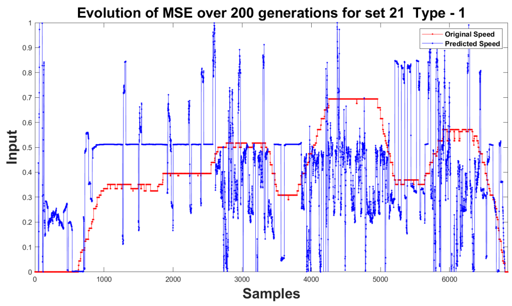

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

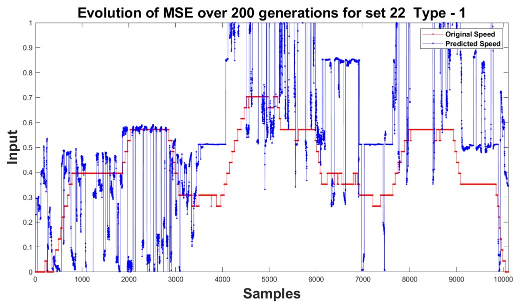

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

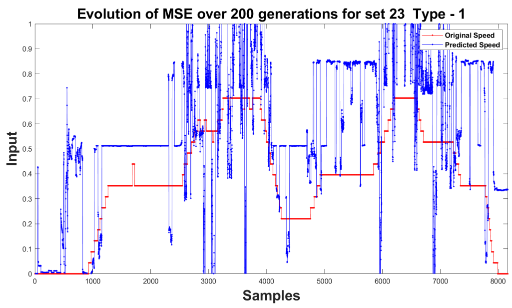

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

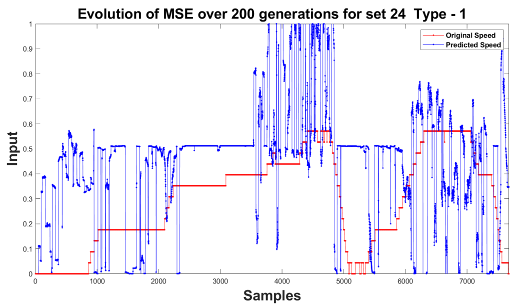

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

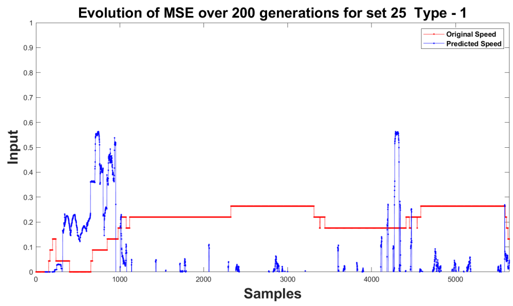

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

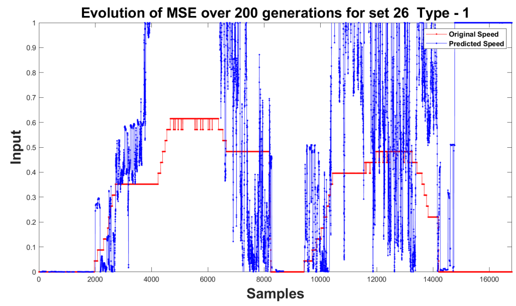

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

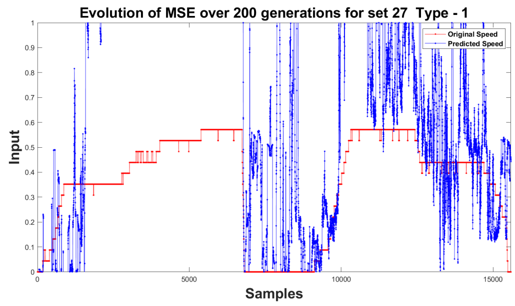

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

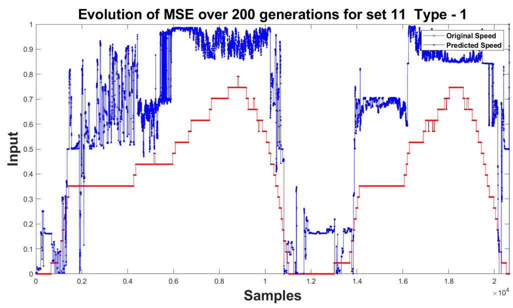

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

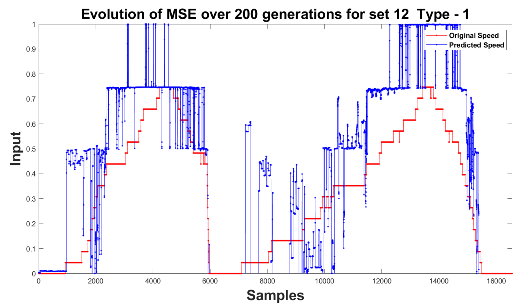


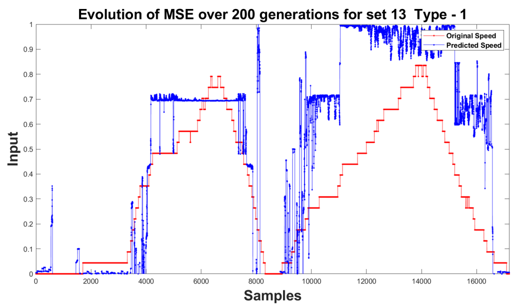


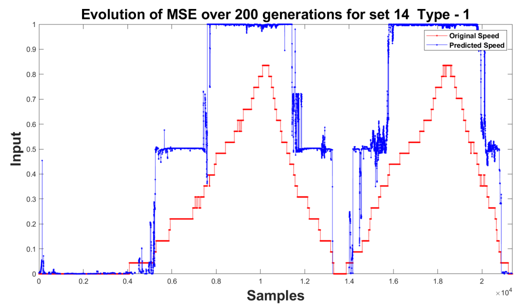


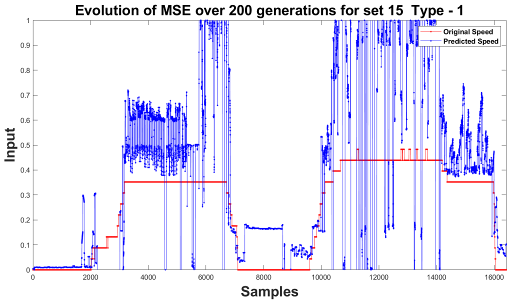
H.2.4 Network 14

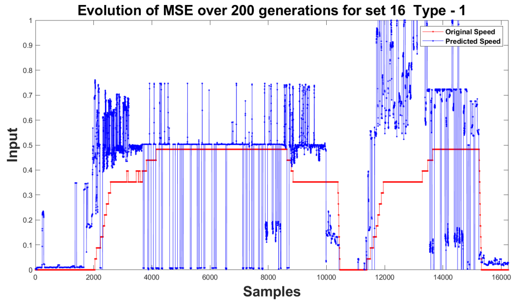


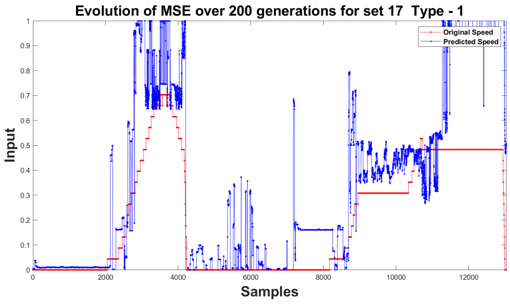


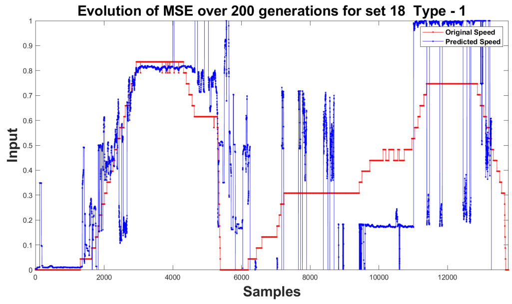


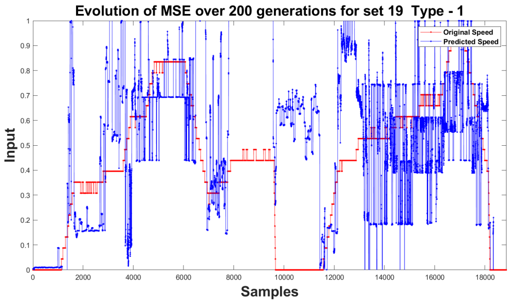


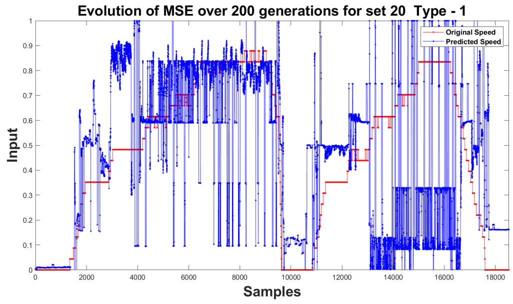

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

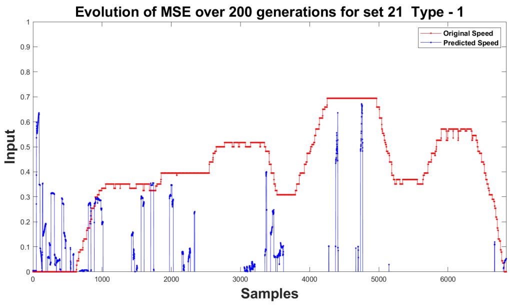

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

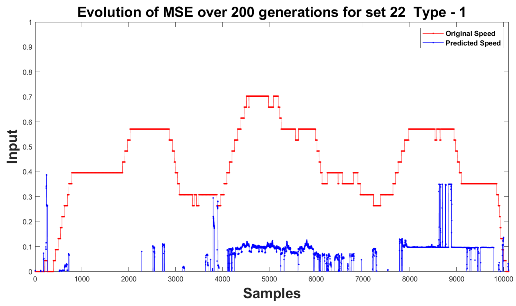

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

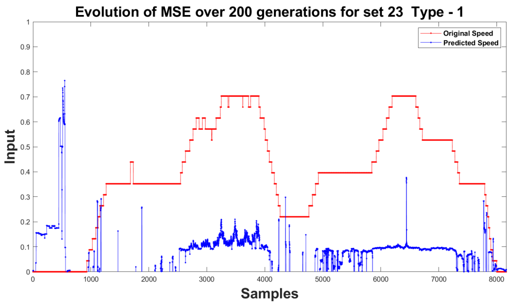

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

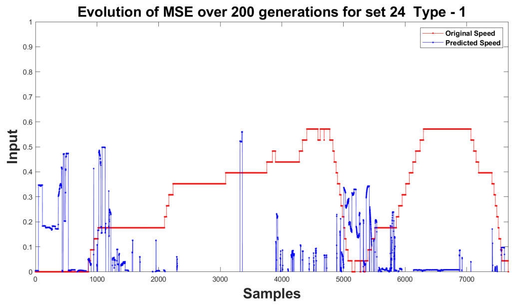

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

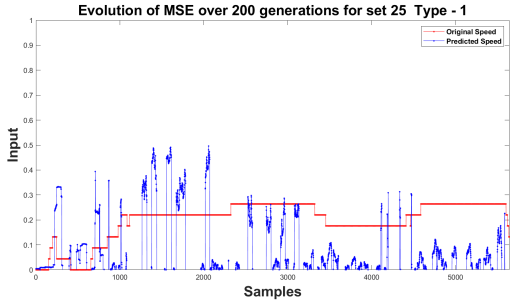

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

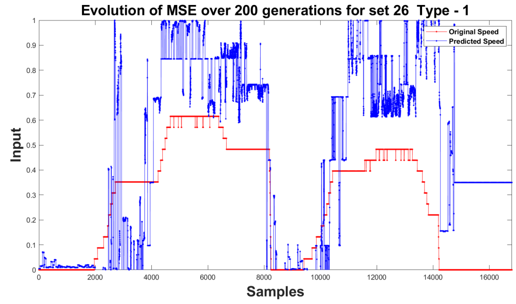

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

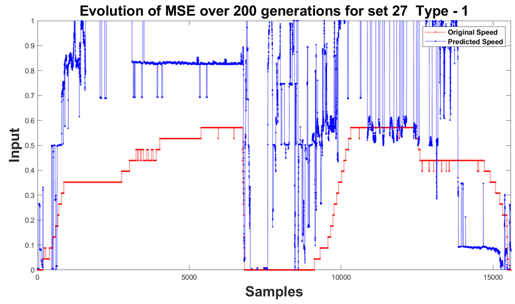

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

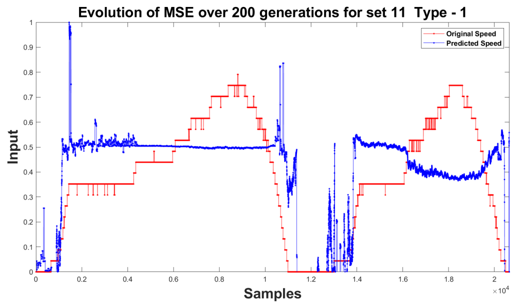

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

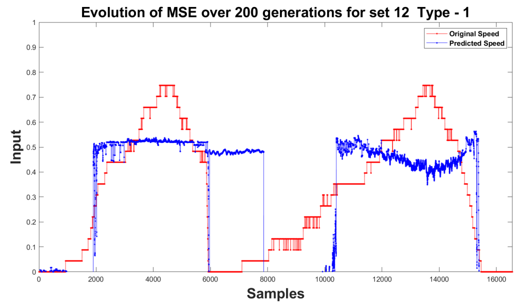


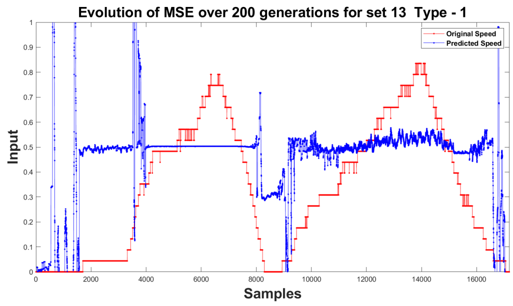


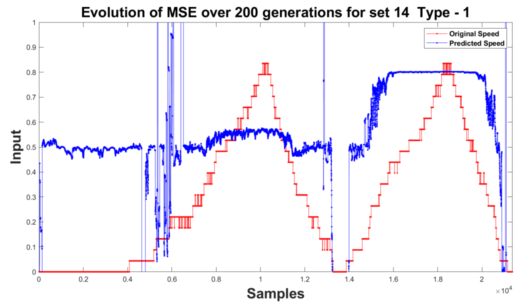


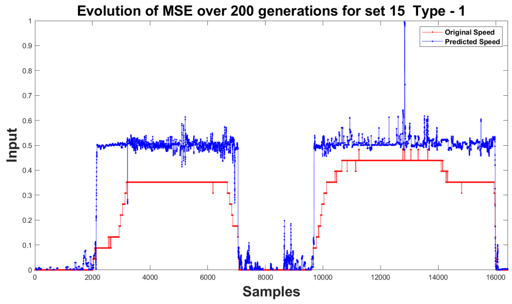
H.2.5 Network 15

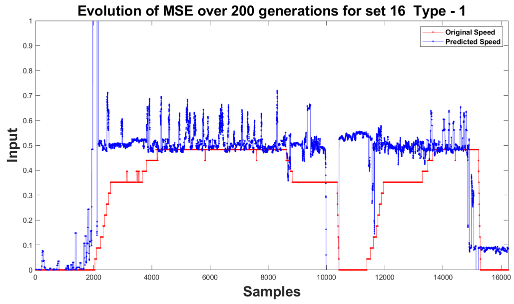


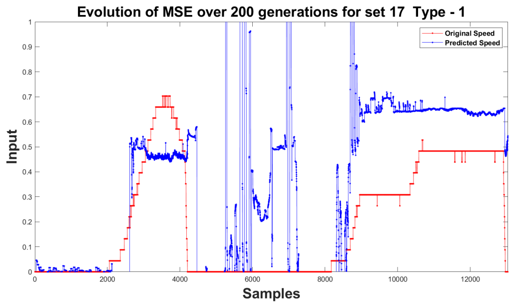


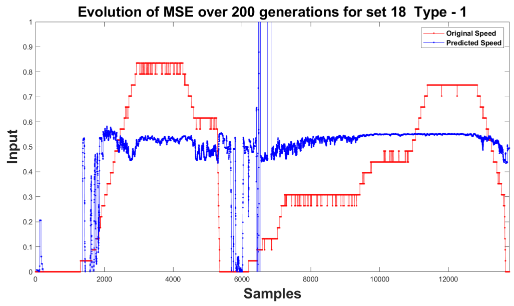


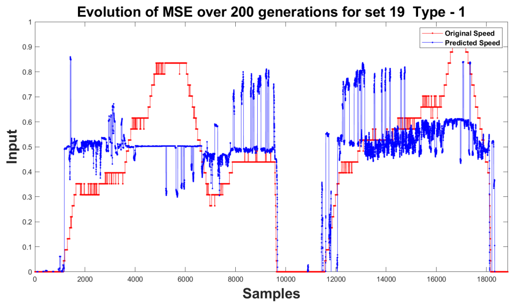


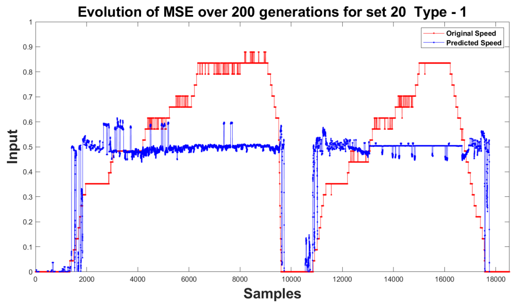

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

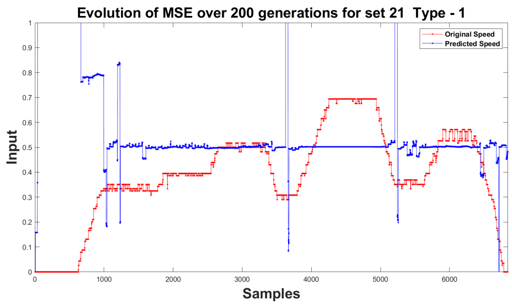

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

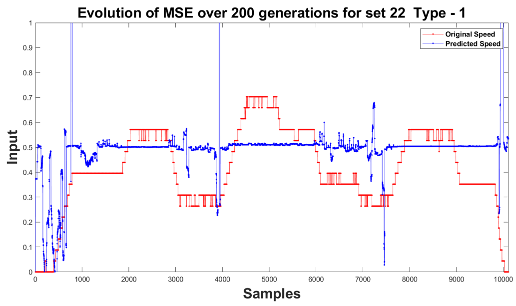

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

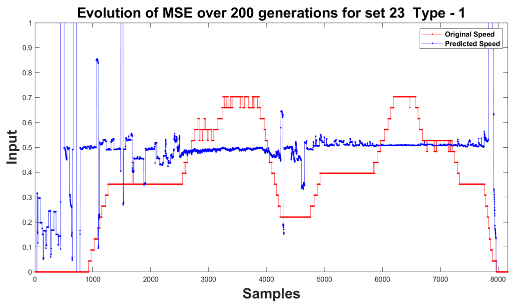

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

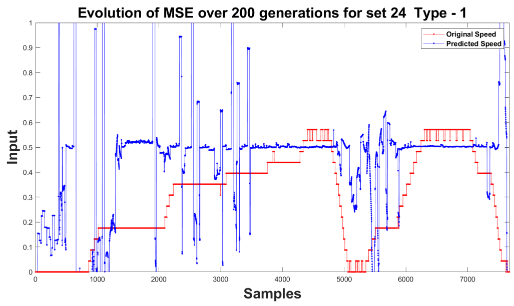

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

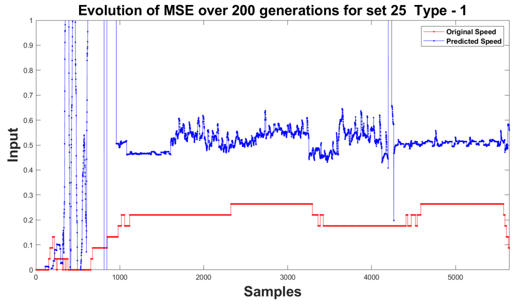

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

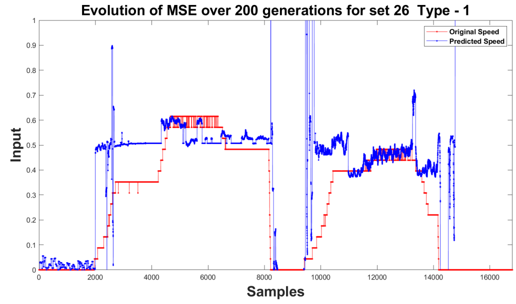

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

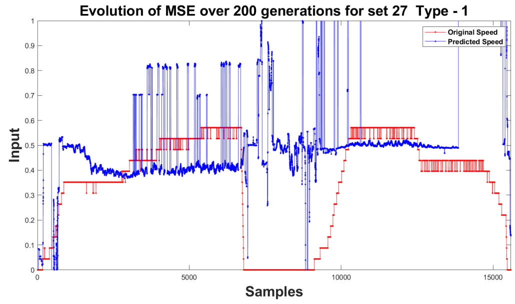

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

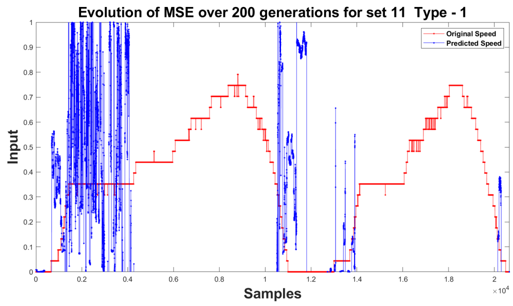

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

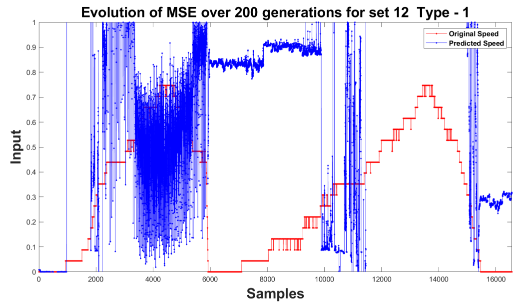


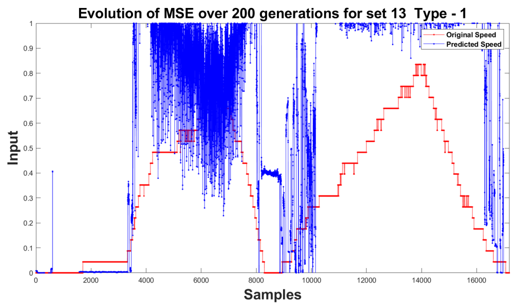


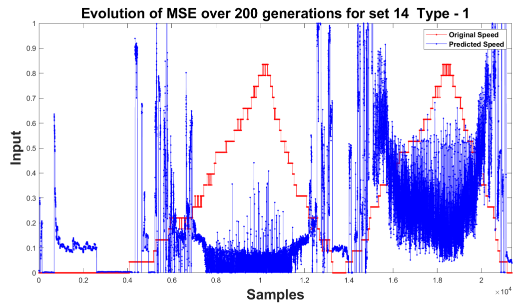


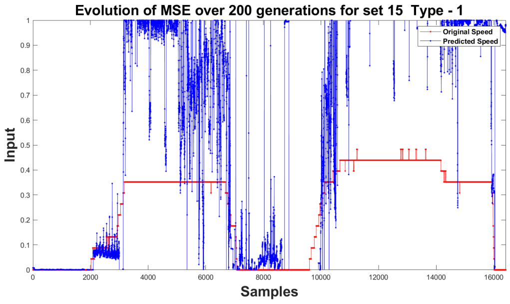
H.2.6 Network 16

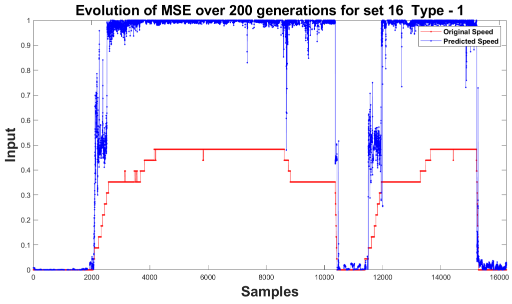


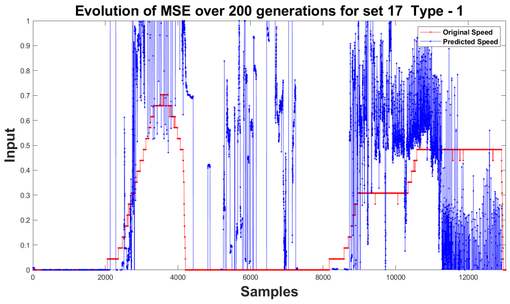


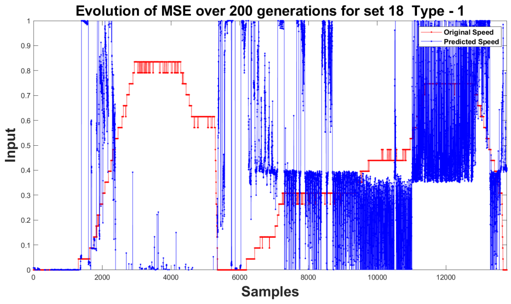


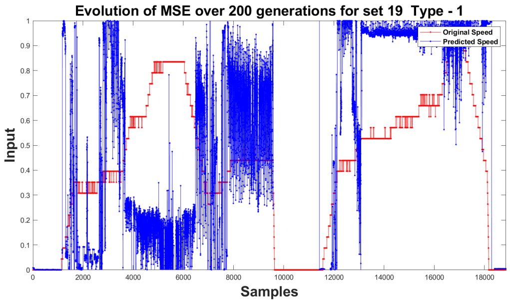


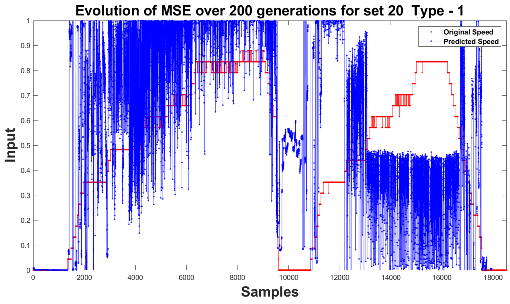

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

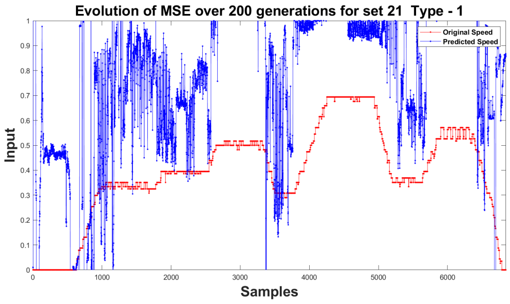

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

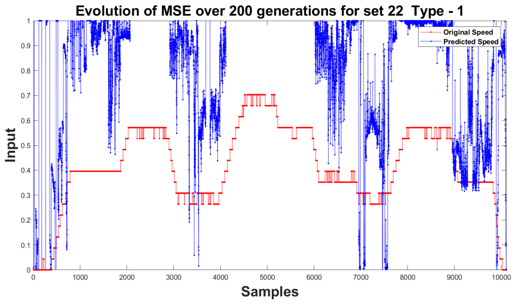

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

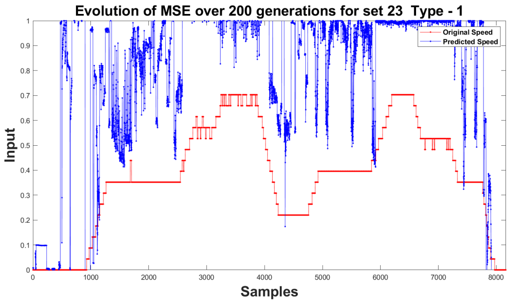

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

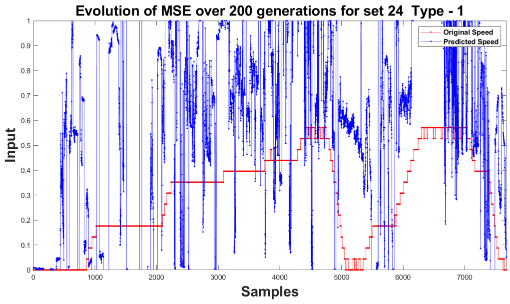

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

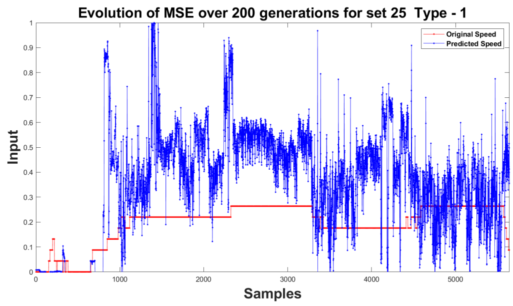

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

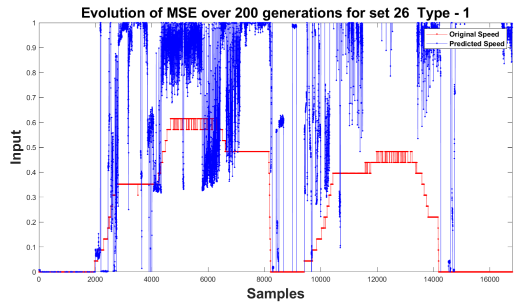

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

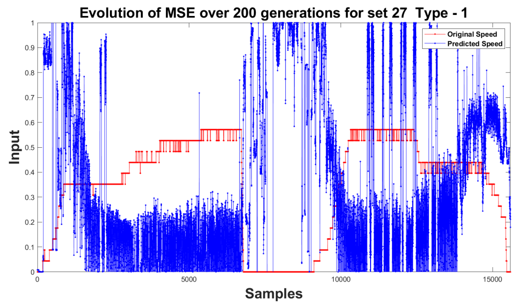

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

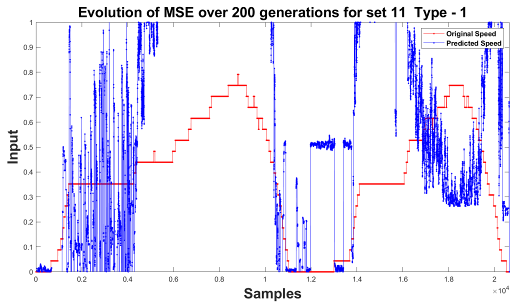

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

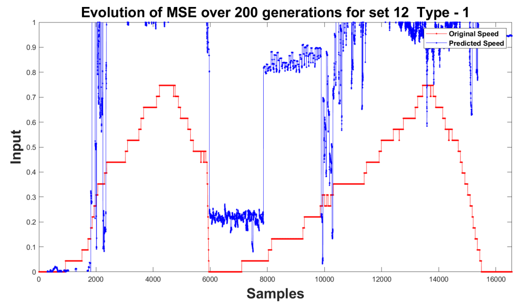


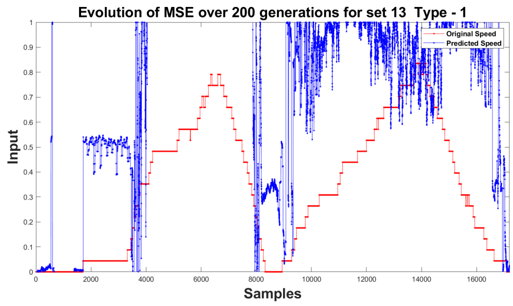


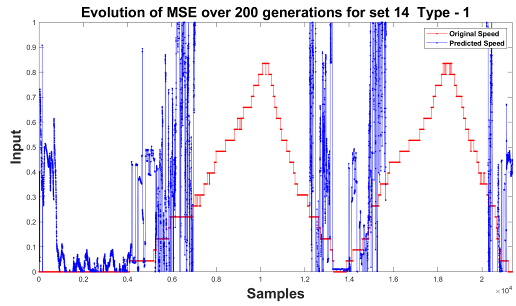


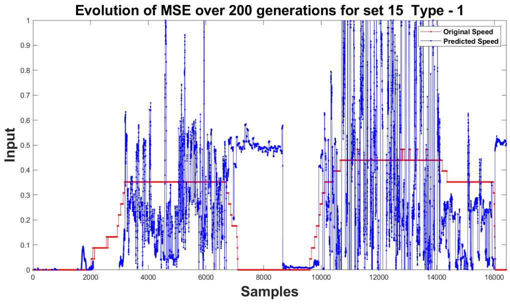
H.2.7 Network 17

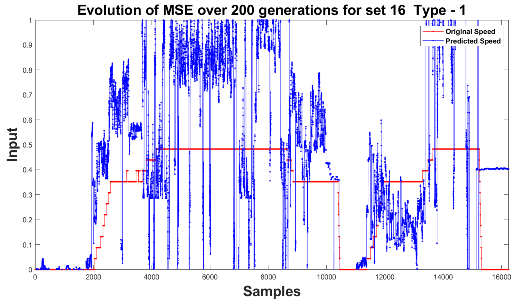


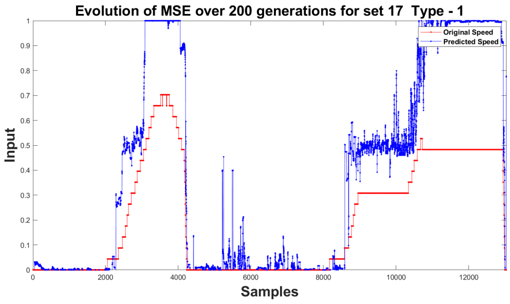


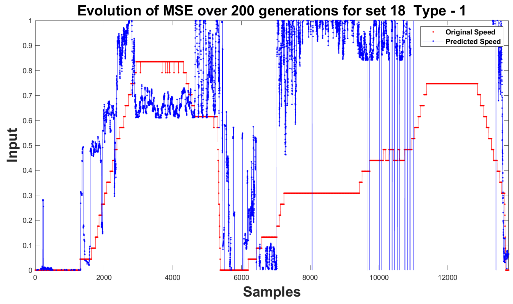


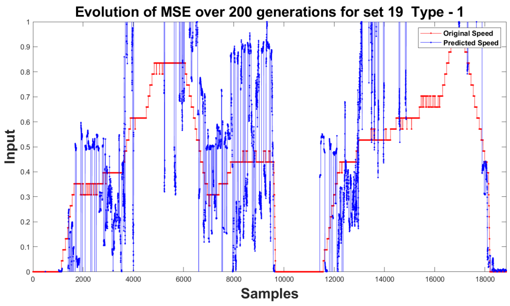


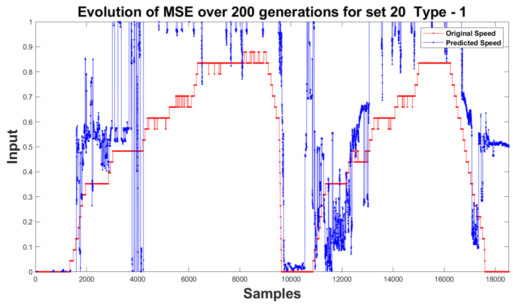

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

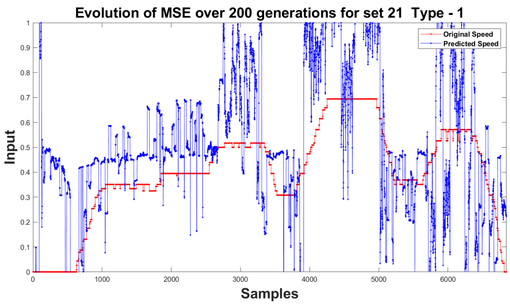

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

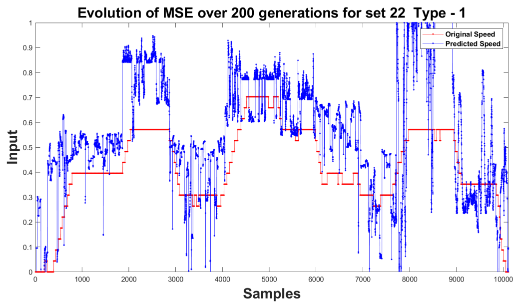

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

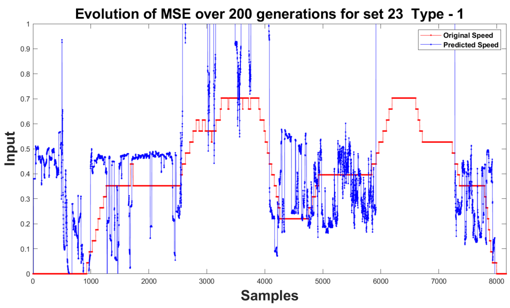

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

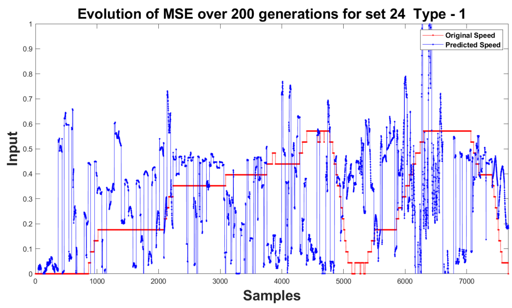

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

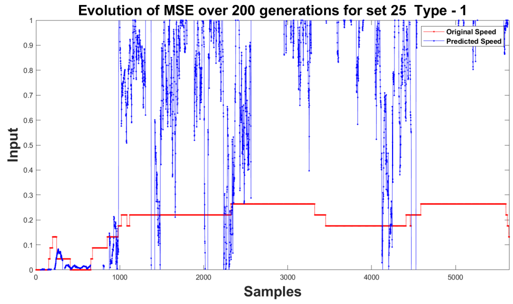

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

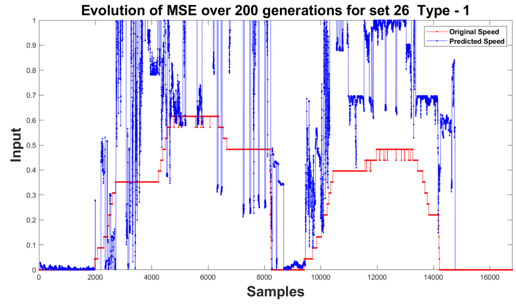

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

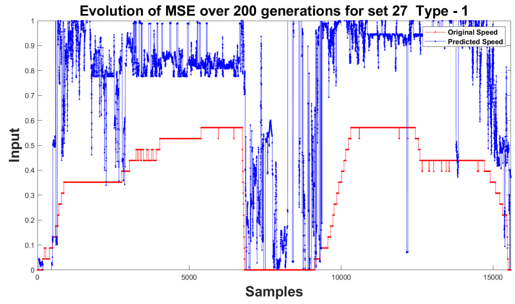

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

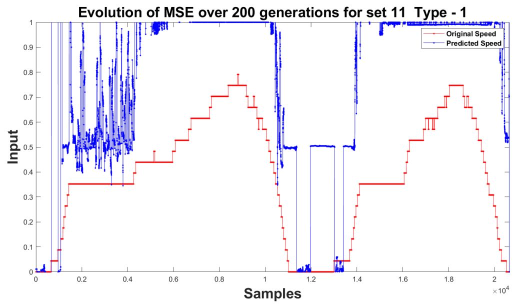

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

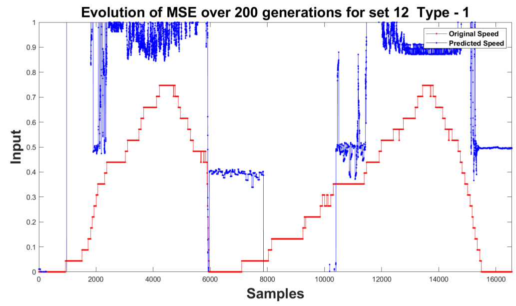


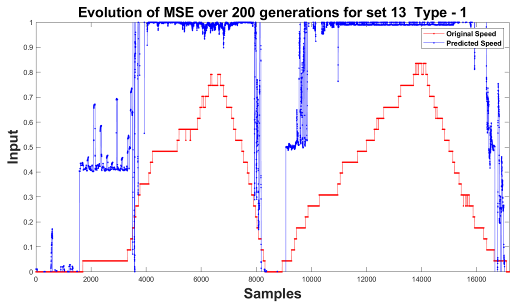


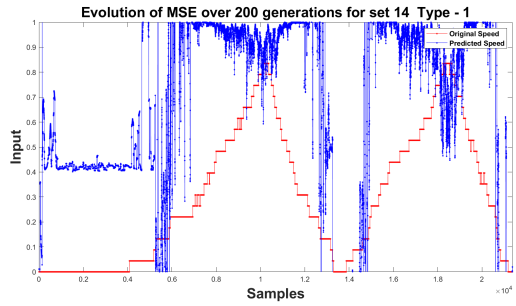


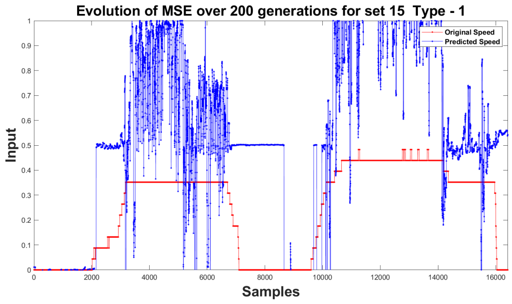
H.2.8 Network 19

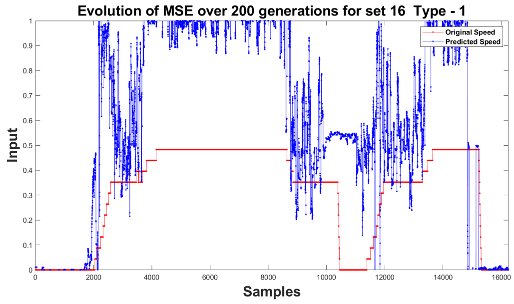


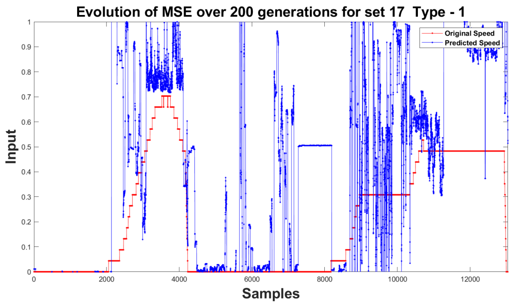


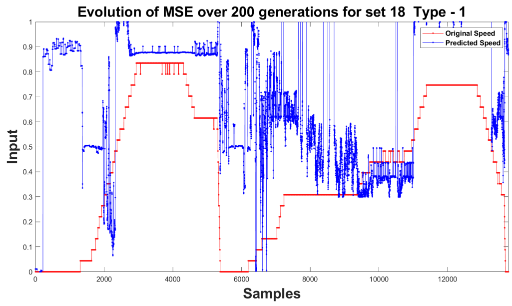


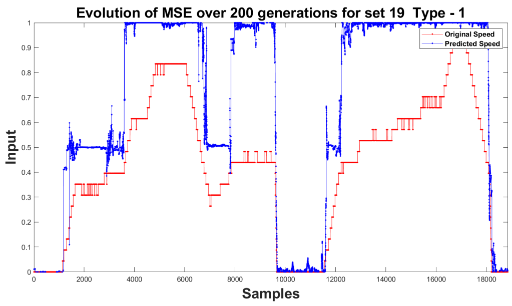


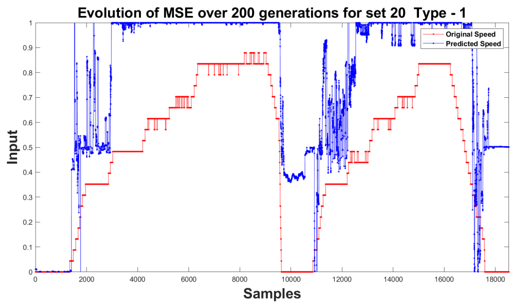

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

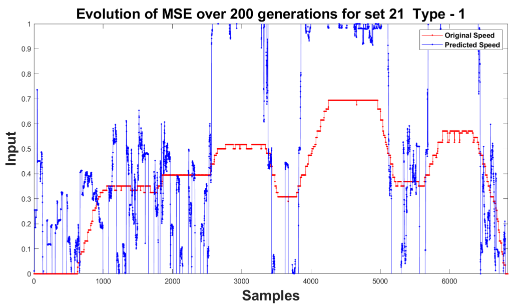

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

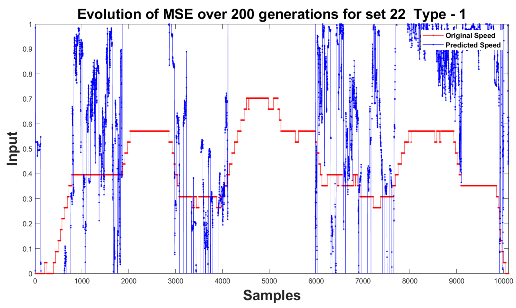

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

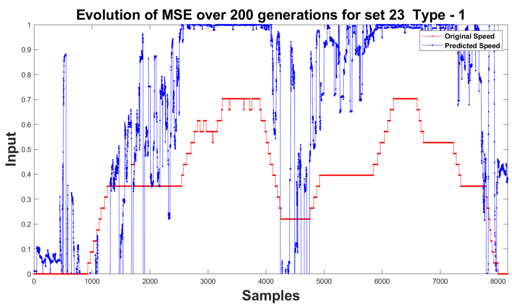

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

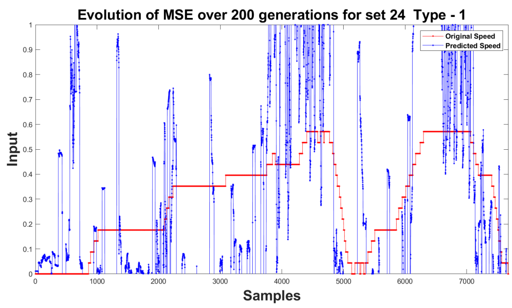

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

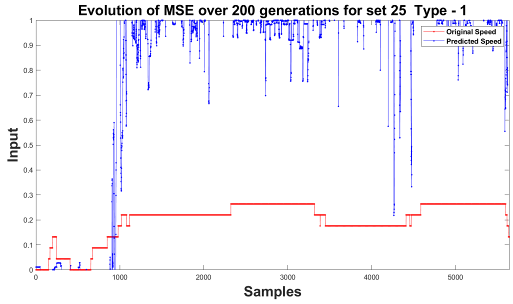

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

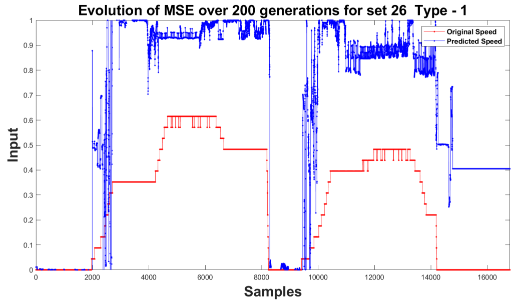

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

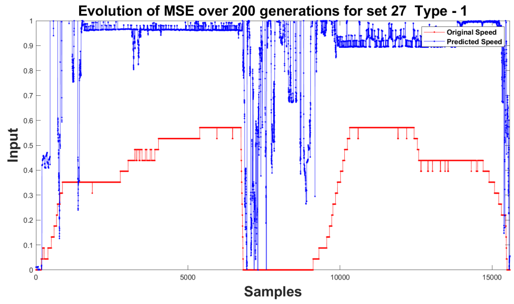

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

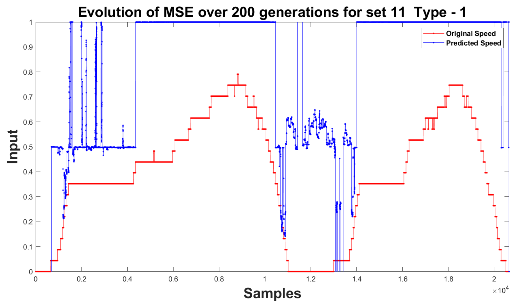

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

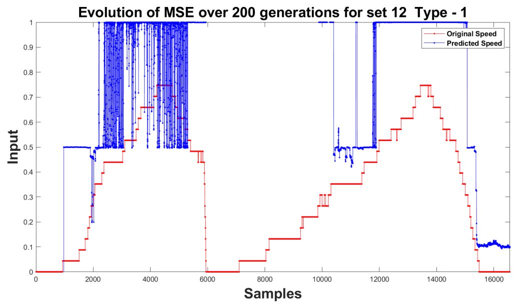


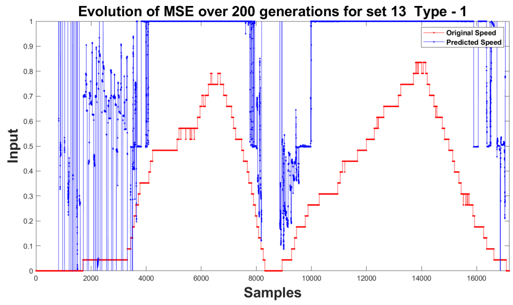


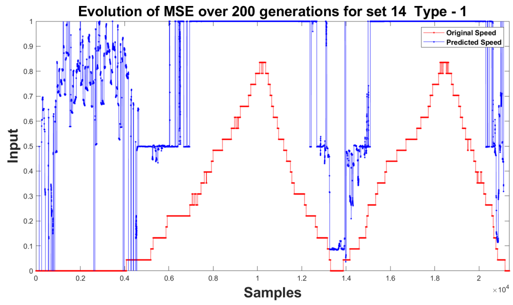


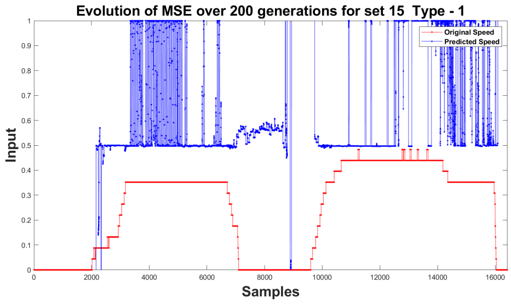
H.2.9 Network 21

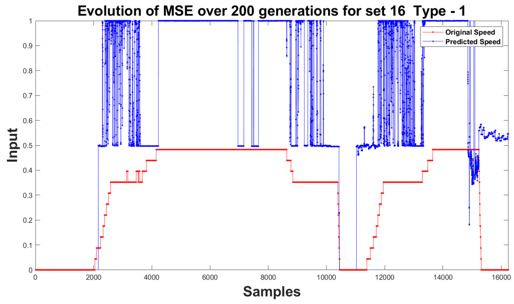


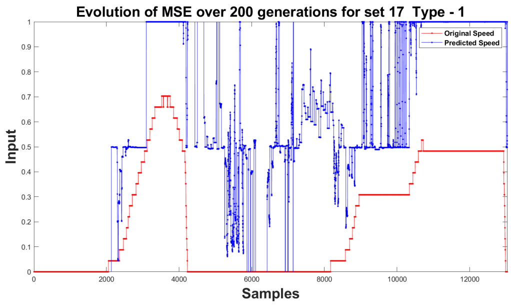


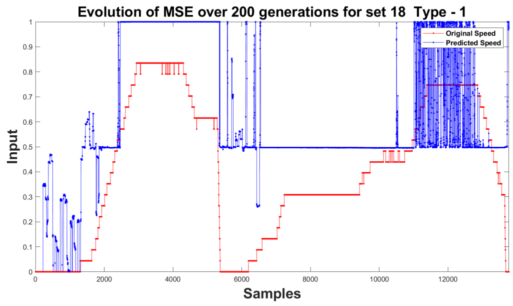


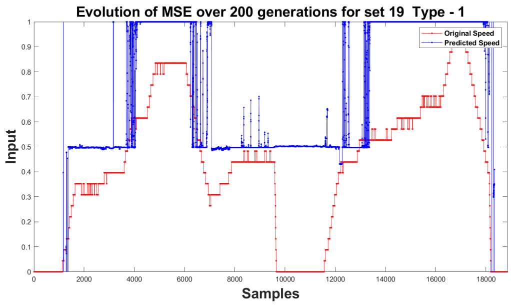


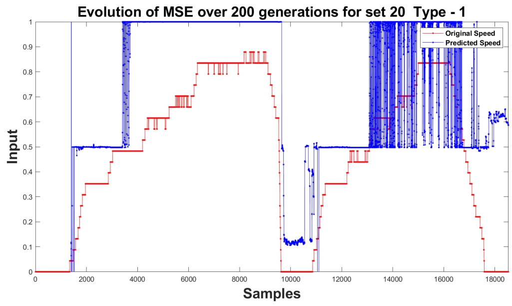

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

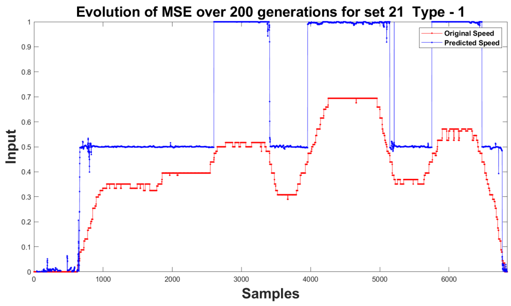

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

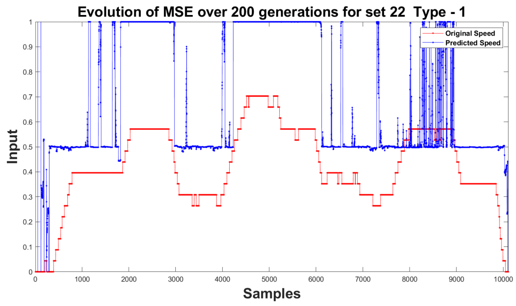

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

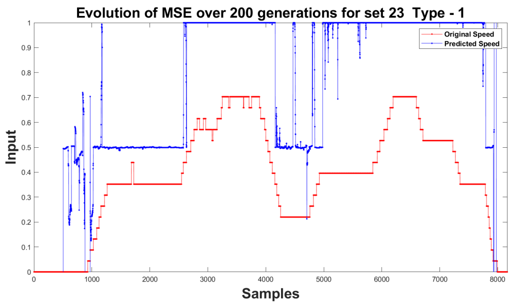

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

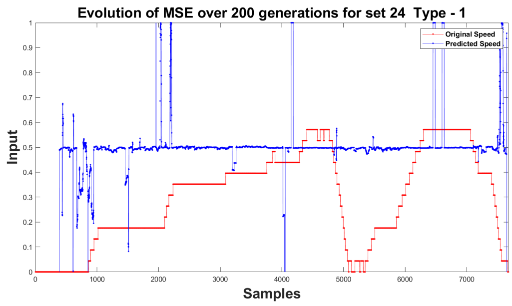

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

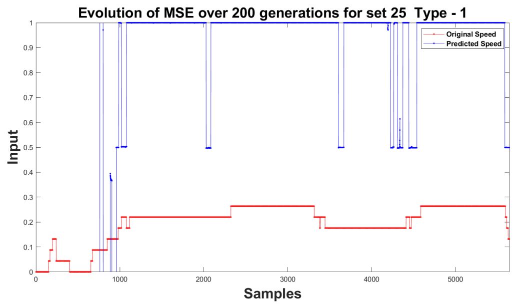

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

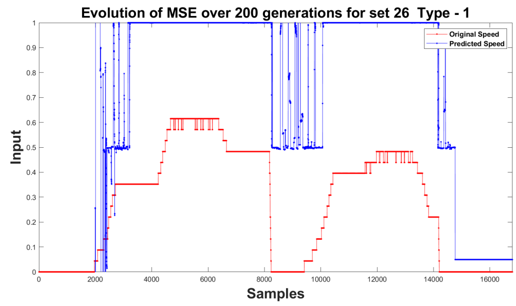

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

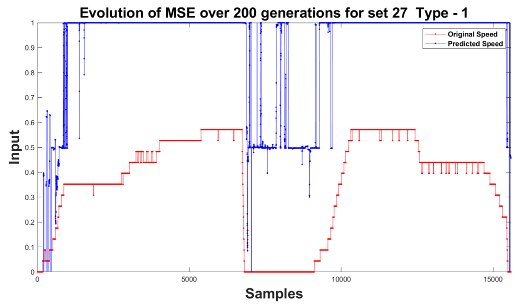

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

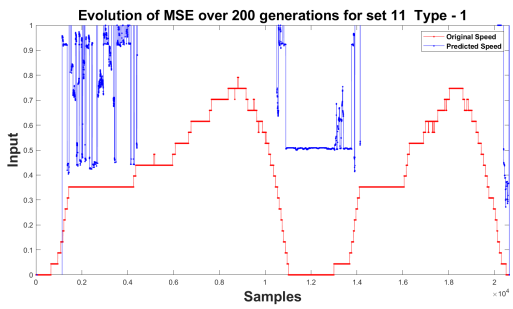

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

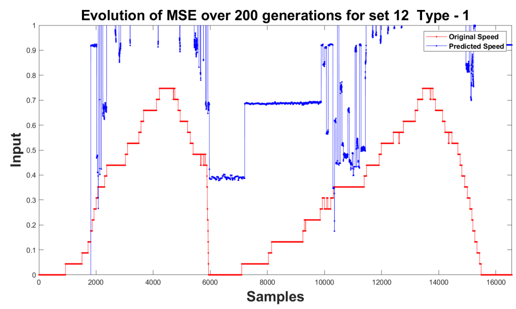


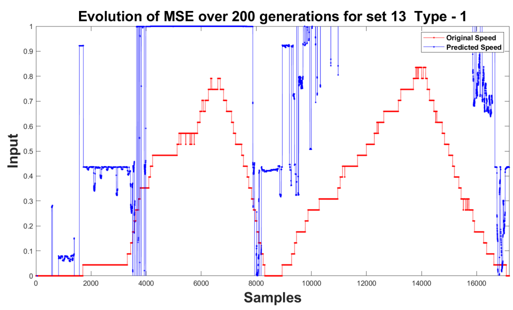


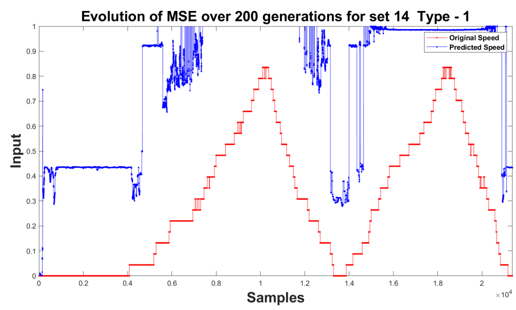


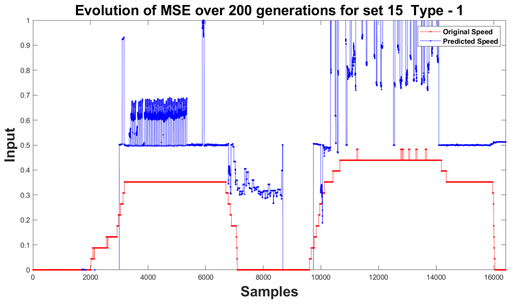
H.2.10 Network 23

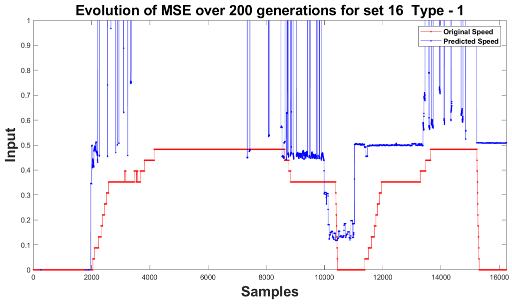


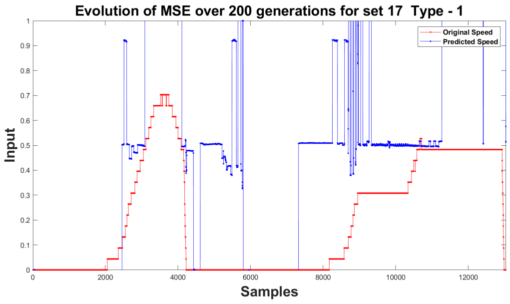


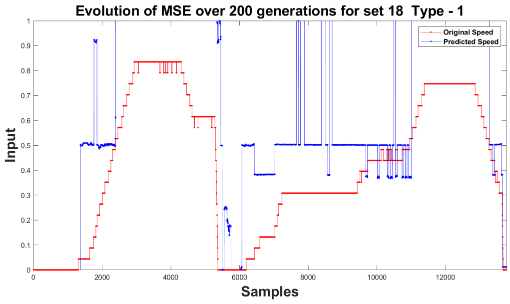


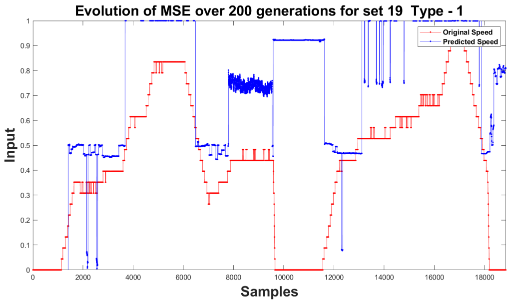


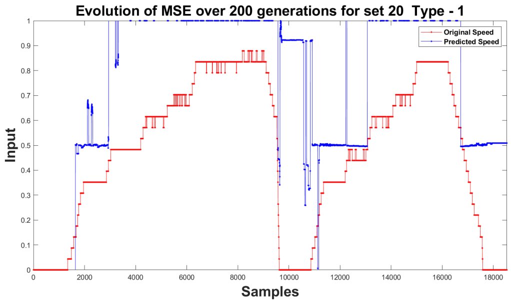

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

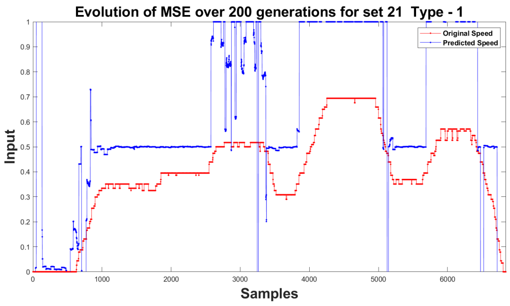

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

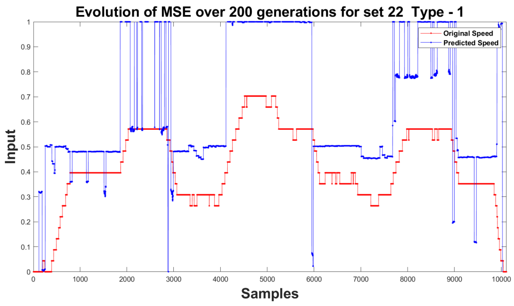

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

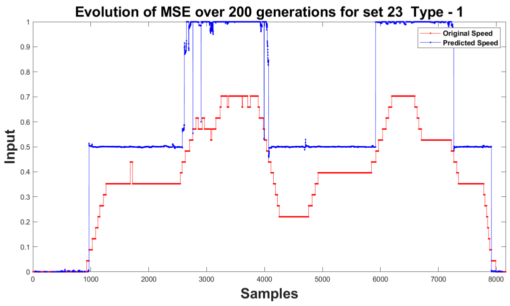

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

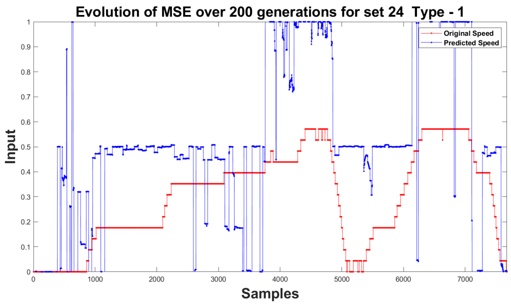

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

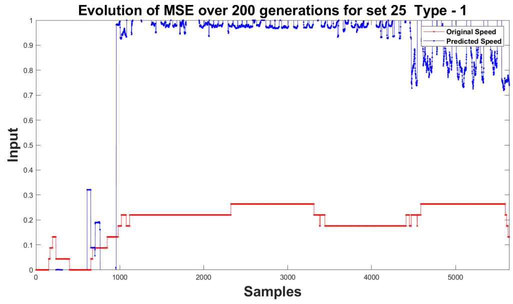

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples

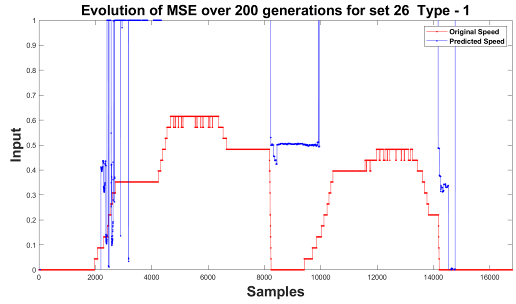

Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

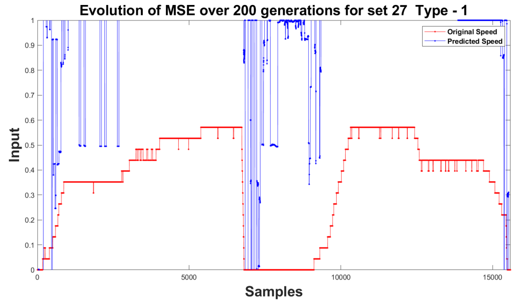

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

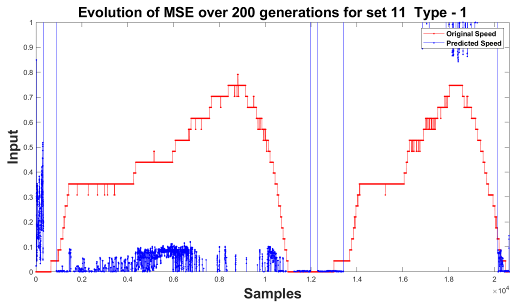

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples

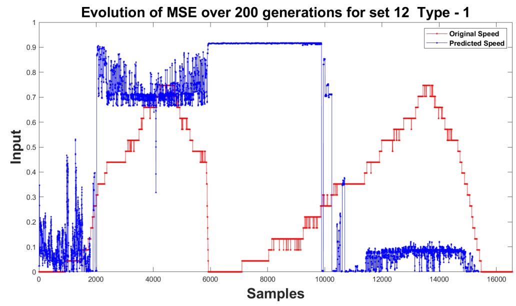


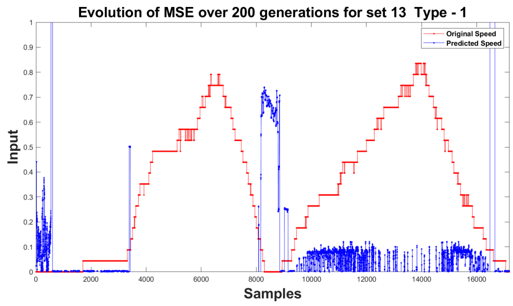


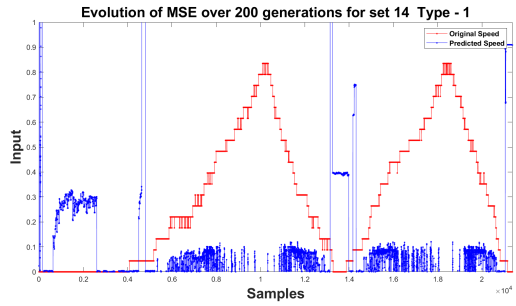


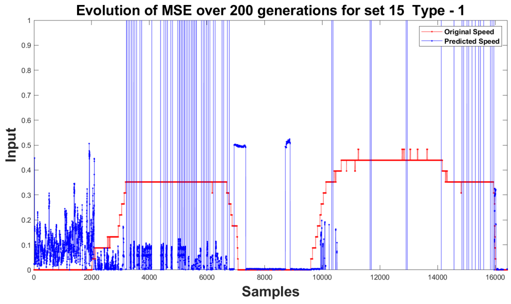
H.2.11 Network 25

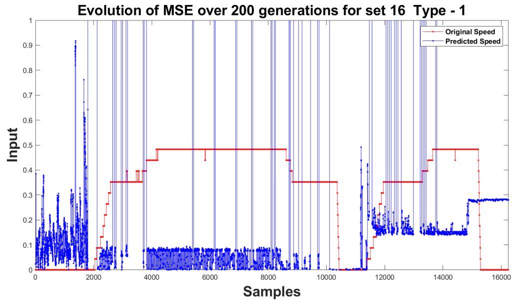


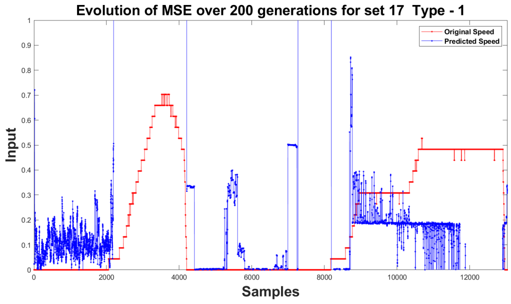


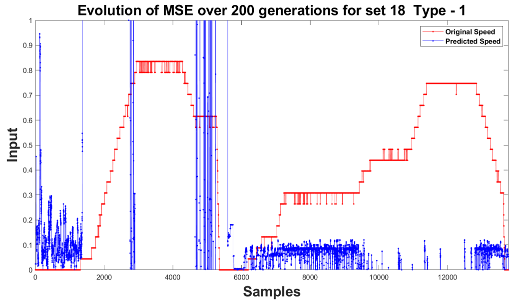


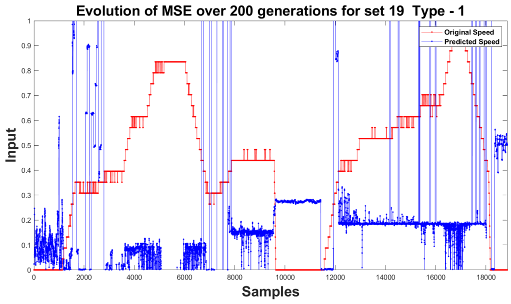


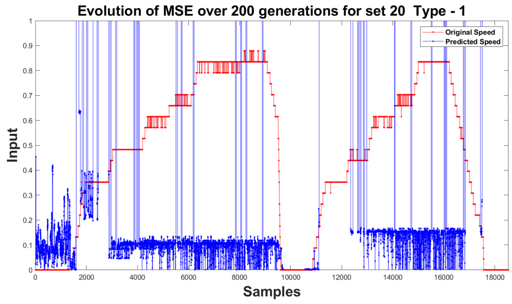

Evolution of MSE over 200 generations for set 15 Type - 1
Original Speed
Predicted Speed
Input
Samples

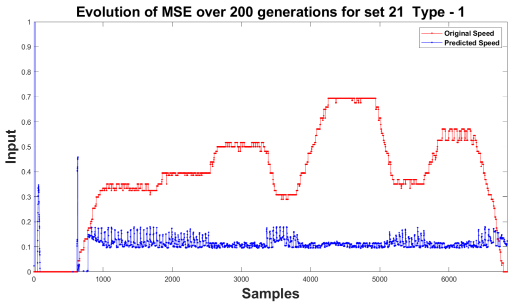

Evolution of MSE over 200 generations for set 16 Type - 1
Original Speed
Predicted Speed
Input
Samples

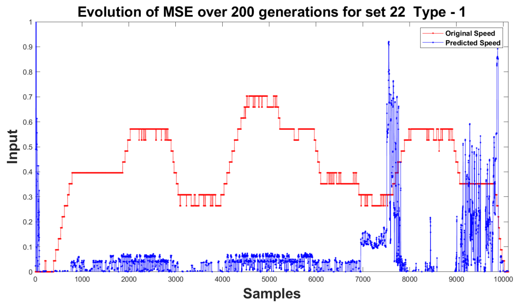

Evolution of MSE over 200 generations for set 17 Type - 1
Original Speed
Predicted Speed
Input
Samples

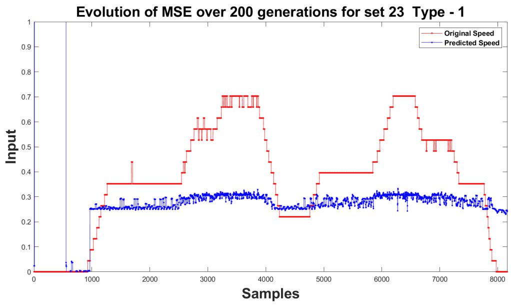

Evolution of MSE over 200 generations for set 18 Type - 1
Original Speed
Predicted Speed
Input
Samples

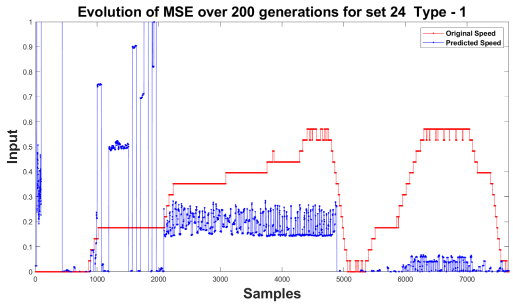

Evolution of MSE over 200 generations for set 19 Type - 1
Original Speed
Predicted Speed
Input
Samples

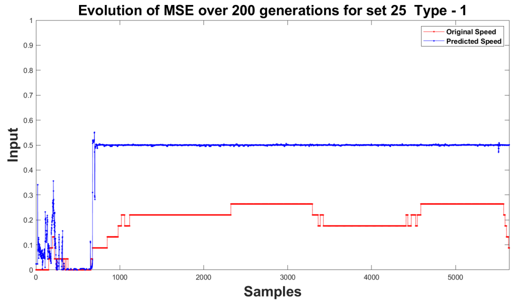

Evolution of MSE over 200 generations for set 20 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 21 Type - 1
Original Speed
Predicted Speed
Input
Samples

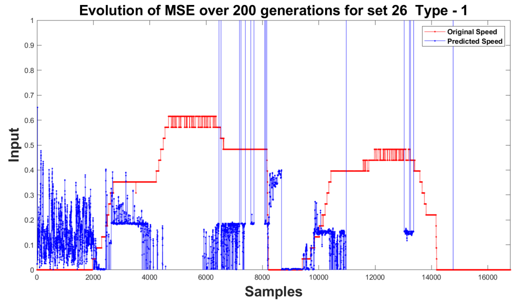

Evolution of MSE over 200 generations for set 22 Type - 1
Original Speed
Predicted Speed
Input
Samples


Evolution of MSE over 200 generations for set 23 Type - 1
Original Speed
Predicted Speed
Input
Samples

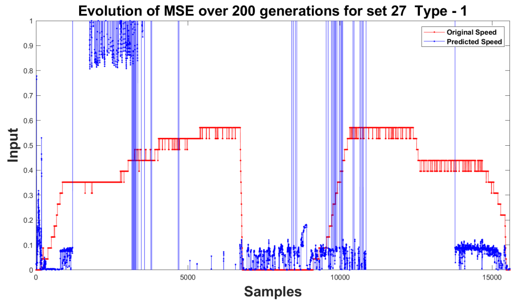

Evolution of MSE over 200 generations for set 24 Type - 1
Original Speed
Predicted Speed
Input
Samples



Evolution of MSE over 200 generations for set 25 Type - 1
Original Speed
Predicted Speed
Input
Samples



Evolution of MSE over 200 generations for set 26 Type - 1
Original Speed
Predicted Speed
Input
Samples



Evolution of MSE over 200 generations for set 27 Type - 1
Original Speed
Predicted Speed
Input
Samples